# Food Fraud

Food fraud: Making specific and efficient use of untapped data inventories



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## Background

A basic categorisation of the term 'food fraud' into legal and structural contexts as well as other terms that are necessary in this area were introduced in the DLG Expert report 'Food Fraud – Food fraud: Possibilities and opportunities for risk minimisation in complex networked value-added chains, 11/2018'[1]. How and, if necessary, the intentions with which, food fraud is typically undertaken was explained there. The following publication supplements these findings by taking a closer look at 'grey areas' between 'optimisations' that are still just within the bounds of legality in food production and boundary transgressions into the realms of intentional deception or even food crime.

Amongst other aspects, this more detailed look is made possible by automated, consistently structured data processing and the continuous evaluation of this with the support of data science, a few examples of which are presented in the text. These clearly show the possibilities offered by systematic, tool-based data processing and analysis for prevention and forensics in food fraud. The enormous potential of the data, which is not yet being optimally exploited in practice at present, is particularly apparent in these areas.

**Important:** The food fraud examples that are used have been selected because they are particularly suitable for illustrating the respective facts. The choice of the examples does not enable any generalised statements to be made with respect to product groups or market players, nor is it intended to insinuate this.

## Tools for preventing food fraud

The early and reliable identification of food fraud[2] is an essential element of strategies for the detection and prevention of food crime. In this case, fraud is usually determined by means of chemical/physical laboratory analysis methods and increasingly also through qualified methods for the sensory assessment of a 'degree of difference' compared to specified target statuses (DoD sensory analysis) (e.g. difference from control test; IN/OUT test). As explained in the DLG Expert report 'Food Fraud, 11/2018', these two approaches can be used in both a targeted (checking a known adulteration) and an untargeted (checking for deviations from defined references and, if necessary, subsequent specification of detected deviations) manner as well as separately or together.

As the core elements for detecting food fraud, chemical/physical laboratory analysis and DoD sensory analysis together essentially form the current 'toolbox' for the detection and prevention of food crime. However, this is not yet adequately equipped for dealing with certain important situations.

## Limits of current tools for preventing food fraud

In order to recognise the possible limits of the current 'toolbox', it is sensible to accordingly structure the topic area of food fraud as an identification point for food crime and to analyse the resulting structural elements as regards their accessibility for the available tools. One of the possible approaches for subdividing food fraud that was introduced in the DLG Expert report 'Food Fraud, 11/2018' was a quadrant structure that is based on manipulation 'mechanisms' and use these to derive resulting risk classes:

- Mechanisms: <u>product</u> manipulation or <u>process</u> manipulation
- Risk classes: food safety hazard exists/does not exist

This subdivision led to a matrix with four 'fraud quadrants', into which various fraud scenarios can be categorised without overlaps.

1 https://www.dlg.org/en/food/topics/dlg-expert-reports/sensory-technology/food-fraud

2 The remainder of the text will refer simply to ‚fraud'

One thing becomes clear when the four quadrants are analysed as regards the sensitivity and specificity of the tools commonly available today for detecting typical forms of fraud: laboratory analysis and process audits provide good service in detecting food fraud in many areas – except in cases that are to be categorised into the **'Process manipulation without food safety hazard'** quadrant. Scenarios in this quadrant are characterised e.g. by:

- the limited 'conclusiveness' of the individual sample due to a lack of statistical legitimacy of the possible conclusions regarding the population from which the sample was taken and
- the effects of technically-related measurement uncertainties, particularly in the proximity of reference values (e.g. specification or limit values).

| **Product manipulation with food safety hazard** | **Process manipulation with food safety hazard** |
|---|---|
| • Melamine in protein mixes<br>• Peanut in hazelnut flour<br>• Glycol in wine<br>• Arylamine dyes in spices | • 'Rework' of non-marketable goods<br>• No pre-run for distillation: 'higher yield' through use of methanol<br>• Use of industrial raw materials (e.g. fats, alcohols, acetic acid) |
| • Hazelnut oil in olive oil<br>• Sawdust in spices<br>• Plaice instead of turbot<br>• Conventional for organic goods<br>• Falsification of documents | • Borderline filling quantity control<br>• Glaze content for frozen goods<br>• Increase in the proportion of external water<br>• Maturation time for hard cheese<br>• Utilisation of specification tolerances<br>• Playing with analytical measurement uncertainty |
| **Product manipulation without food safety hazard** | **Process manipulation without food safety hazard** |

*Figure 1: Quadrant of possible food fraud methods*

On the whole, it is at best 'difficult', but often practically impossible, to make clear black-or-white decisions in food fraud scenarios in this quadrant. In practice, the limits of the tools that are commonly available today are revealed in food law assessments that are correct in terms of content, but do not clearly support decisions, such as:

- 'The determined pH value of 4.53 **falls slightly below** the pH value of 4.6-5.0 defined as per the **product specifications.**'
- 'The prepared percentage of cranberries of 5.0% **deviates slightly** from the product specifications (5.5 – 10.6%).'
- 'We would like to point out that, at 220 mg/kg, the determined content of tin exceeds the maximum content of 200 mg/kg pursuant to the Annex to Commission Regulation (EC) No. 1881/2006. Taking the extended **measurement uncertainty** into consideration, however, it is **not significantly** exceeded.'
- '>Residue< with a concentration of 5.9 $\mu$g/kg, which exceeds the permissible maximum content of 5.0 $\mu$g/kg, was detected in the submitted sample. [...] Taking an **analytical range of variation** of 37% into consideration, however, this maximum content is **not significantly** exceeded.'

Results such as these, i.e. in connection with self-checks, are not ideal for managers. Since the 'toolbox', regarded objectively, does not enable any more far-reaching information, the laboratory service provider is unable to provide the reliable basis for decision-making that is actually expected. While no lack of marketability is determined and defects, deviations and comments in the 'grey area' are pointed out in detail, for instance, this information can only be used systematically and efficiently to improve affected products or as an early warning indicator for subsequently implementing 'preventative measures' in a very small number of cases. Food fraud in the 'Process manipulation without food safety hazard' quadrant therefore presents the established, methodological 'toolbox' with barely manageable challenges and offers potential food fraudsters what is (still) a relatively low-risk loophole for gaining economic advantages. This is therefore referred to as the 'dubious quadrant' in the following

## Food fraud – or grey area?

The exploitability of the 'dubious quadrant' for food fraud essentially arises due to three circumstances:

- Lack of statistical meaningfulness of individual samples for inductive conclusions,
- Focus of the test plans on value-adding and value-reducing attributes that are directly accessible with measurement technology, and
- Process-related measurement uncertainties, particularly in the area of relevant nominal values.

Certain factors increase the likelihood of specific deception, up to and including food crime, occurring by exploiting the situation in the 'dubious quadrant'. Products that meet one or more of the following conditions appear to be particularly at risk, for instance:

- They have very high trade volumes,
- They are homogenous,
- They are sold in homogenised form,
- They can be produced using easily dosed recipe percentages.

Such products give rise to various possibilities for food fraud in which actual intent is very difficult to prove today even in the event of a corresponding finding in a random sample, e.g.:

- Stretching with native constituents (e.g. additional grinding of stalk constituents),
- Including inferior goods in marketable goods while adhering to or just slightly exceeding any limit values, and
- Exhausting permissible or tolerated 'technically unavoidable' variations in specification values[3].

In part, the existence of the 'dubious quadrant' is actually unintentionally fostered due to legal regulations or established market practices for certain product groups: for example, the German Pre-packaging Regulation (FPackV) permits (randomly occurring) underfilling according to defined statistical patterns[4], while the 'Guidelines for Meat and Meat Products'[5] specify unspecified ranges of variation for contents of value-adding constituents in various locations (e.g. Section 1.72 'The connective tissue protein-free meat protein content [...] is approx. 20%.'). In accordance with the definition, fraud in the 'dubious quadrant' does not endanger the fundamental safety of food. Insofar as such cases are detected at all, they are barely present in the media.

However, this must not be used as grounds for reducing the 'search effort' in this quadrant. The reason for this is that, firstly, this can lead to significant financial losses for the companies concerned, which would also result in impacts on end consumers in the form of price adjustments that have become 'necessary'. Secondly, it is becoming clearly apparent that supply chain-oriented standards such as IFS and BRC are increasingly applying control pressure on market players and will demand check and control systems that can reliably intercept fraud of all categories, with the result that the 'food fraud or grey area?' question can be clearly answered by companies in the future.

So how can food fraud be detected and prevented in good time if the current 'toolbox' is unable to provide any clear decision-making criteria? By extending the methodological 'toolbox' with the potential of data and its targeted, systematic management.

## Combination of laboratory analysis, process audit and data science

In the event that a lack of marketability is determined, the procedures within companies are clearly designed for consumer safety and the aversion of losses. They lead to robust safety and corrective measures such as e.g. quarantining goods prior to sale up to and including public recalls of goods that have already been brought into circulation.

Conversely, laboratory analyses and assessments of the marketability of food rarely lead to the determination of a lack of marketability: for non-processed foods, the rate of 'not marketable' complaints is usually less than 1% of all test reports that are produced. In the case of mixed products and processed food, the rate is usually only slightly higher and lies in the single-digit percentage range depending on the individual product group, amongst other aspects.

Conversely, the number of test reports that determine fundamental marketability, but issue critical comments on the food law assessments in the form of e.g. determined measurement results, the degree to which specification values are complied with or determined sensory deviations, etc. regularly veers clearly into the double-digit percentage range.

3 Preferably 'varying' in favour of the supplier, of course

4 https://www.gesetze-im-internet.de/fertigpackv_1981/FertigPackV_1981.pdf, z. B. 1.1.1

5 http://www.deutsche-lebensmittelbuch-kommission.de/sites/default/files/downloads/leitsaetzefleisch-2.pdf

So far, the content of food law assessments of this type of test report has hardly ever been documented and evaluated holistically in a clearly structured manner in any company. Accordingly, reactions to purportedly or actually critical content in the assessment texts of the test reports differ, since they are dependent on the behaviour of individual employees and other factors that vary according to the specific company. Consequently, correct reactions in the sense of effective quality management are due more to remarkable individual performances than the result of methodical strategic actions. Many companies have extremely large inventories of data and information, and often spend six- to seven-figure sums of money per year to procure, manage and analyse these. Nevertheless, they are only primarily able to exploit their potential selectively for sustainable improvement and prevention – namely wherever breaches of specifications/regulations or a lack of marketability are ascertained and documented on the basis of facts by (service-providing) laboratories. Conversely, information that does not fulfil this tough restriction in terms of the form in which it is provided is usually merely filed with a sense of unease and is therefore degraded from a potentially valuable wealth of data to an extensively worthless data deposit.

The causes of this are due, firstly, to the (technical) language that is used, because the individual formulation of comments in the test report makes semantic content and the actual statements difficult for machines to access. Secondly, existing psychological barriers are disruptive factors that prevent the still relatively new technologies of machine learning from being integrated into the analysis and management processes of daily business operations.

Insofar as corresponding projects have been launched in companies, however, it generally emerges that the storage formats and media that are commonly used for test reports (e.g. PDF, word processing, paper, etc.) hamper the automated further processing of the data and its use for targeted quality and risk management. The reason being that automated semantic analysis can only be commenced once the relevant texts are available in a standardised form (file format)[6]. Content/linguistic challenges are additionally thrown up in terms of grammatical and spelling mistakes, technical vocabulary and the service provider-specific designations of laboratory parameters and units (due in part to various computer systems), and in the structure of sentences and paragraphs, etc. Further processing steps are therefore sensible or even necessary in order to efficiently, consistently and automatically exploit the full potential of a wealth of data hidden in a (large) quantity of test reports to achieve added value. Amongst others, the following measures have proved appropriate:

- Generation of higher-level semantic contexts, e.g. ‘cow’ is an ‘animal’, ‘milk’ is from ‘cow’ (unless another ‘animal’ is explicitly mentioned in the context) and is therefore ‘of animal origin’, etc.[7]
- Establishment of correlations between text elements and specifically identified individual measured values[8] within a test report.
- Provision of specific measured values, warning levels, sentiment analyses, etc. over several products and longer periods of time[9].
- Connection of tools for automatically evaluating external web sources, such as warning portals, weather stations, etc.[10]
- Connection of company and service-providing laboratories that operate with laboratory information management systems (LIMS) that offer export functions for test report information in CSV and/or XML formats.[11]

Various options for specifically optimising the detection of fraud processes arise even if only parts of the machine learning technologies available today are used for automated linguistic (semantic) evaluations of test reports, because the power and potential of data are readily apparent even in ‘small’ tools.

6 Provision must not be limited to project environments, but must function reliably and robustly in daily operations and cope with the volumes of test reports that are produced.

7 Potentially affected goods in the own portfolio can then be determined automatically for external warnings.

8 If the text refers to an ‚increased microbial load‘, for example, the link to specific measured values can be used to automatically ascertain which microbes are specifically referred to in the text.

9 Besides time series analyses, this enables broader populations and therefore the use of inductive statistical methods in the early detection of potentially food-adulterating processes.

10 Extends the spectrum of leading indicators beyond one‘s own company, particularly if higher-level semantic links have been established (e.g. rain during the harvesting season => increased risk of mould in grain => increased risk of contamination due to mycotoxins in grain products).

11 Extensively simplifies the provision of test report information in a consistent, machine-processable form, if necessary.

## Practical examples and applications of the new ‚data analysis' tool

Machine learning offers multiple possibilities for analysing test report data. The fundamental benefit will be illustrated on the basis of a relatively simple example in the following.

The product group of meat and sausage products, specifically homogenised or chopped products in raw or boiled condition, will be analysed for this purpose. A meaningful number of test reports from various sources were retrospectively evaluated and examined to determine which measurement variables (parameters) were mentioned in negative contexts in assessment texts for this product class with a processing-related, consistent risk profile for certain attributes.

To do this, the parameters mentioned in negative contexts were transferred to a 'tag cloud' or word cloud, whereby the font size for a term was selected according to the absolute number of its mentions across all test reports (see Figure 2).

A form of visualisation that is used far too rarely is its extension to dynamised visualisation with a 'time window' that can be moved over the data inventory. This would mean that the word clouds of the various test reports would be arranged consecutively in chronological order, so changes and therefore offers an intuitively understandable element in implementing early warning systems in practical quality control.


*Figure 2: ‚Tag cloud' of negative parameters from test reports for meat & sausage products (note: the colour and position of a term within the word cloud are purely aesthetic in character and, unlike the font size, have no meaning in content terms).*

The application of dynamised word clouds therefore made it clear that some of the parameters contained in the initially shown word cloud[12] appear at all times and are conspicuous[13], whereas others only occur cumulatively for a limited time.

A detailed evaluation revealed that, since the autumn of 2019, there was a strong correlation between the accumulation of critical references to 'listeria' in meat and sausage products in general and the 'Wilke case'[14] [15] [16]. It must be emphasised that the measurement results and test reports available for the evaluation did not reveal any statistically significant increase in the listeria load of the analysed products, but that an increased number of critical assessments of precisely these parameters 'in the grey area' (assessment texts) had nevertheless occurred, something that was clearly recognisable when the evolution of the word cloud was examined.

This methodology enables e.g. quality managers of a distributor that has this class of chopped products in its portfolio and procures them from several suppliers to use the terms appearing in word clouds as indications of increased testing needs for its own traded products or suppliers. This circumstance would not be so easy to recognise with conventional forms of data provision. If the potential of the data is used skilfully, however, such indications can be found with a few clicks of a mouse, even by users without detailed knowledge of the products.

12 Unfortunately, this can only be shown as a static word cloud in a printed medium, of course

13 I.e. they were represented with a large font type

14 https://umwelt.hessen.de/presse/pressemitteilung/bericht-zum-fall-wilke

15 https://umwelt.hessen.de/sites/default/files/media/hmuelv/sachstandsbericht_des_landkreises_waldeck-frankenberg_causa-neu_wilke.pdf

16 https://umwelt.hessen.de/sites/default/files/media/hmuelv/bericht_rp_kassel.pdf

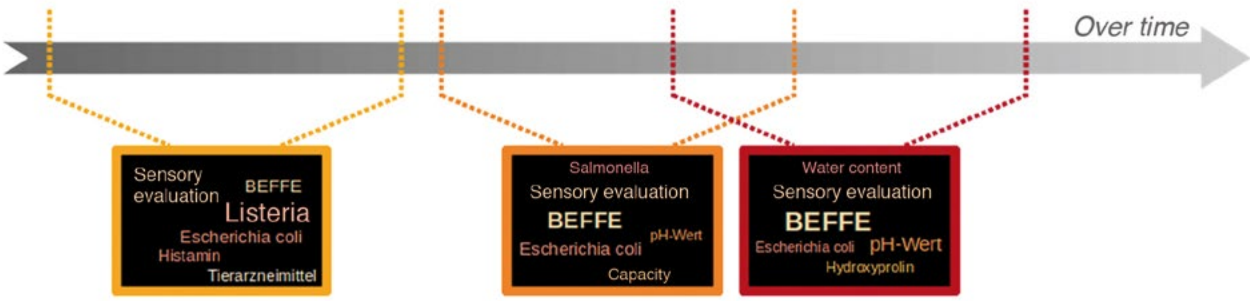


*Figure 3: Dynamic visualisation of ‚tag clouds' of negative parameters from test reports*

Commercially available data acquisition methods use data science tools and machine learning (ML) methods to undertake company-specific processing, harmonisation and enrichment[17] of the totality of all available test reports following a system 'training phase' and to make the data available in accordingly processed form after evaluation.

The following figures have been taken from screen visualisations of a web interface[18] and show initial, simple possible uses. In this case, the user has selected a familiar 'traffic light system' to simply distinguish the risks identified in the test report.

According to the traffic light system, the colours have the following meanings:
●/green = no complaint
●/yellow = critical indications
●/red = serious complaint or lack of marketability

The assignment of traffic light colours can be based entirely on complete test scopes; alternatively, however, the ML algorithms that are used can also evaluate specific parameters or parameter combinations in isolation.

By applying this to all of a supplier's risk-related products[19], traffic light representations can be automatically generated on the user interface, enabling systematic quality issues to be easily identified. For the situation shown, the system's ML algorithms were set to the parameter 'BEFFE' (the one that occurs most frequently in the respective word cloud shown above). 'BEFFE' stands for 'connective tissue protein-free meat protein' and represents the protein content of the pure muscle flesh as a dimension of the quality of a meat product[20]. The percentage of BEFFE in extensively homogenised samples is usually regulated by guidelines (see above) or specified in greater detail and can be easily checked during production. The actual BEFFE content is checked in the laboratory using indirect methods.

While deviations in the direction of BEFFE values that are lower than specified or required in the guideline usually lead to critical indications ●/yellow for individual samples due to the sample's lack of statistical relevance, they only lead to the discovery of severe deviations ●/red in rare cases – and consequently a possible situation from the grey area of the 'dubious quadrant'.

In addition to the traffic light system, the system that is shown uses characters and geometrical shapes (tick in a 'green' circle, exclamation mark in a 'yellow' circle and exclamation mark in a 'red' triangle). This serves to enable reliable identification even on black-and-white printouts of the screen content or for users with red/green colour blindness.

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17 E.g. with environmental data from warning portals, weather reports, etc.

18 The basic Risksniffer GmbH system was used in this case because the authors, as the founders of the company, are particularly familiar with this system. It is entirely possible that other systems enable similar data processing and evaluation.

19 Semantic meta information, etc. is used here.

20 E.g. https://www.lebensmittelwissen.de/lexikon/b/BEFFE.php

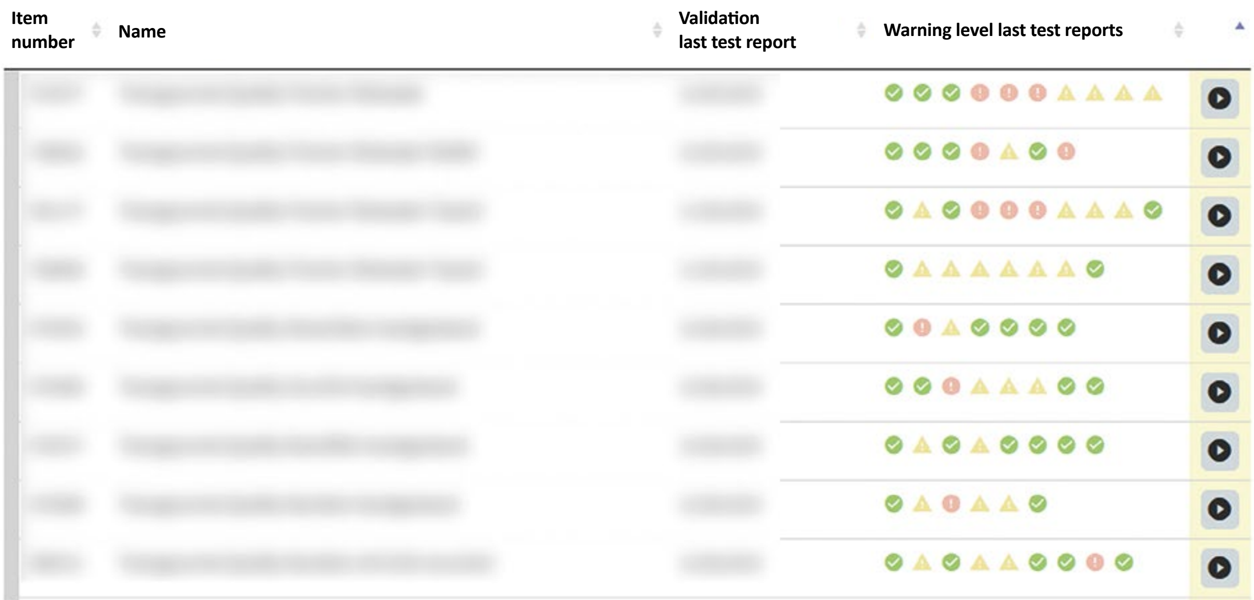


*Figure 4: Case example 1: evaluation of test reports and warning levels*
*(Note: illegible areas in the screenshots are due to data protection reasons.)*

### Case example 1: effect of quality-improving measures

All documented samples (laboratory analyses with test reports) of all articles with a comparable risk profile[21] in the defined analysis period are evaluated as regards BEFFE statements with this system. To do this, the samples are evaluated based on measured values, notes in the natural language assessment texts and metadata generated by the system, and the result assessment is displayed with the corresponding symbol (see Figure 4). Each row in the screenshots corresponds to a specific product; only the content of the ''Warning level last test reports' column is of interest for the example: the result symbols are sorted in chronologically descending order, i.e. the oldest sample/test report from the period analysed is located on the far right; accordingly, the most recent sample/test report is located on the far left[22].

Even this simple chronological classification of the machine-generated evaluations (condensed to the described symbols) immediately shows that critical assessments were the rule rather than the exception from the very start for some of the products with this risk profile. Based on the accumulation of critical indications and serious complaints, it additionally becomes clear that the quality of several products in this group was intermittently inadequate. In turn, the respectively current test reports (far left) are consistently without complaints, which can be interpreted as an indicator of the effectiveness of implemented improvement measures. In order to validate this interpretation, it is necessary to maintain a comparable monitoring intensity in the future. Since corresponding systems undertake this fully automatically, this task can be easily integrated into the daily quality management work routine.

21 In this case, selection is carried out automatically by the system on the basis of metadata, but automatically suggested selections can be adjusted manually or replaced entirely by manual selections.

22 In this visualisation, a firmly established lack of marketability is also shown as a red circle with an exclamation mark for the overall assessment.

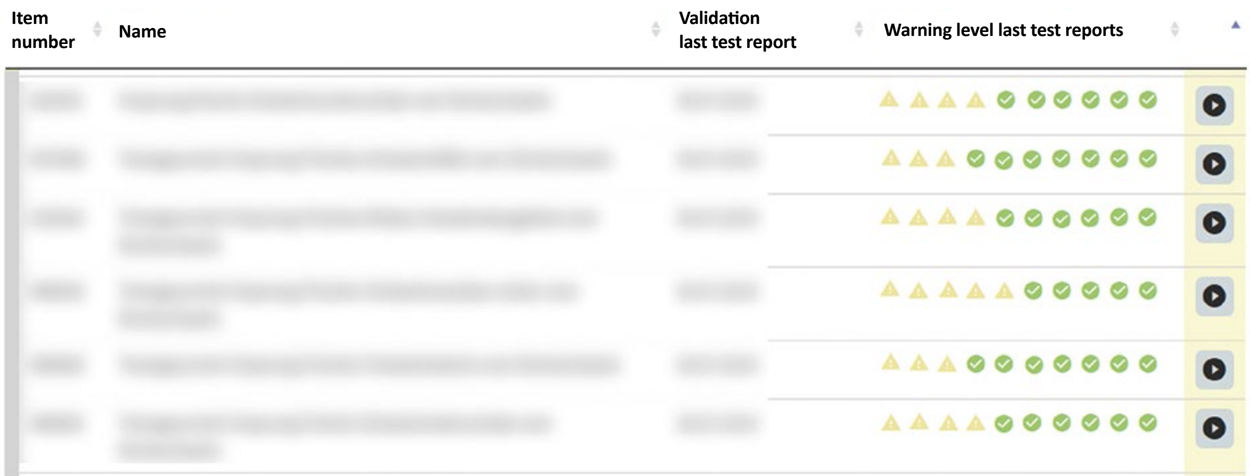


*Figure 5: Case example 2: evaluation of test reports and warning levels*
*(Note: illegible areas in the screenshots are due to data protection reasons.)*

### Case example 2: detection of emerging quality erosion

Cases of gradual quality erosion can certainly leave behind signs that remain undetected over a long period of time in the ‘dubious quadrant’, but which could have been identified earlier with modern tools.

A pattern that is typical of this situation can be seen in the case of the articles compiled and analysed in Figure 5 - insofar as the tools that are used are able to ‘read between the lines’ of food law assessments. After meeting expectations in full (specifications, guidelines, etc.) at the start of supply (oldest test reports, therefore shown on the right in the respective row), indications of quality defects become more frequent after a long period of time; while these have not reached ‘non-marketable’ status, they have nevertheless caused laboratories to issue critical indications[23] in relation to BEFFE in the report text.

In the daily work routine of companies, such a change often remains undetected across an entire product class with today’s tools. This enables market players to manipulate food for a long period of time without sanctions, at the expense of the customer and ultimately consumers.

As in case example 1, it is also apparent here that even relatively simple ML-based evaluations can offer significant advantages in proactive quality and risk management. Nevertheless, expertise is also required to use modern tools.

### Increased efficiency

The operational value of data science/ML-based evaluations lies in the increases in efficiency that are achieved by focusing a company’s limited resources on checking specific suspected cases instead of a broad-based random sampling method that – as has already been explained – in any case encounters tight system-immanent limits in the ‘dubious quadrant’. Above all, these tight system-immanent limits of modern tools are significantly extended by data science/ML-based approaches due to the fact that predominant trends can be revealed, despite the limited statistical significance of the individual results, insofar as several articles with a comparable risk profile are compared with one another, as in the example for the quality-indicating parameter BEFFE.

23 Sentiment analyses such as those implemented in the system used here enable automatic and highly reliable distinction between positive and negative mentions of parameters in report texts.

Although a ‘harsh verdict’ regarding BEFFE is hardly ever found in a test report, the simultaneous, repeated occurrence of critical comments in this regard offers sufficient ‘statistical evidence’ for an initial suspicion that this supplier is acting with intent or is passing on an unidentified defect.

On this basis, quality control resources can then be specifically invested in more detailed analyses and plausibility checks. If the suspicion of specifically stretching cost-intensive pure muscle flesh using cheaper substitutes is corroborated in the context of such measures, e.g. by checking weighing protocols during audits, this would almost certainly equate to intentional food fraud in the ‘Process manipulation without food safety hazard’ area. Without the use of data science/ML, it is extremely unlikely that this case of food fraud from the ‘dubious quadrant’ would have been systematically detected and, even if it had, only with a great deal of product experience on the part of the employees and with parameters that belong more to the category of ‘usual suspects’.

So that the case examples remain consistent with one another, the ‘traffic light system’ was again used for visualisation. The condensed food law assessment texts could also have been structured as word clouds, because these particularly facilitate data interpretation in the sense of the following:

- Without any product knowledge whatsoever, the word cloud (Figure 2) clearly showed that BEFFE should be examined in greater detail based on the font size alone.
- As soon as parameters often appear in assessment texts, they appear in word clouds irrespective of whether they are ‘usual suspects’ or ‘absolute one-offs’, as a result of which even users with extensive product knowledge can obtain valuable additional information without a great deal of effort.

The upshot is that, to shed light on the ‘dubious quadrant’, innovative methods of data visualisation, a partial area of data science, can provide tools that access the potential of the data in a user-friendly and intuitive way for the benefit of companies.

### Case example 3: emerging quality erosion and bought-in articles

A finally case study shows how the traffic light visualisation of evaluation results can be used for supplier management issues. Figure 6 shows various products with a comparable risk profile from a specific supplier.

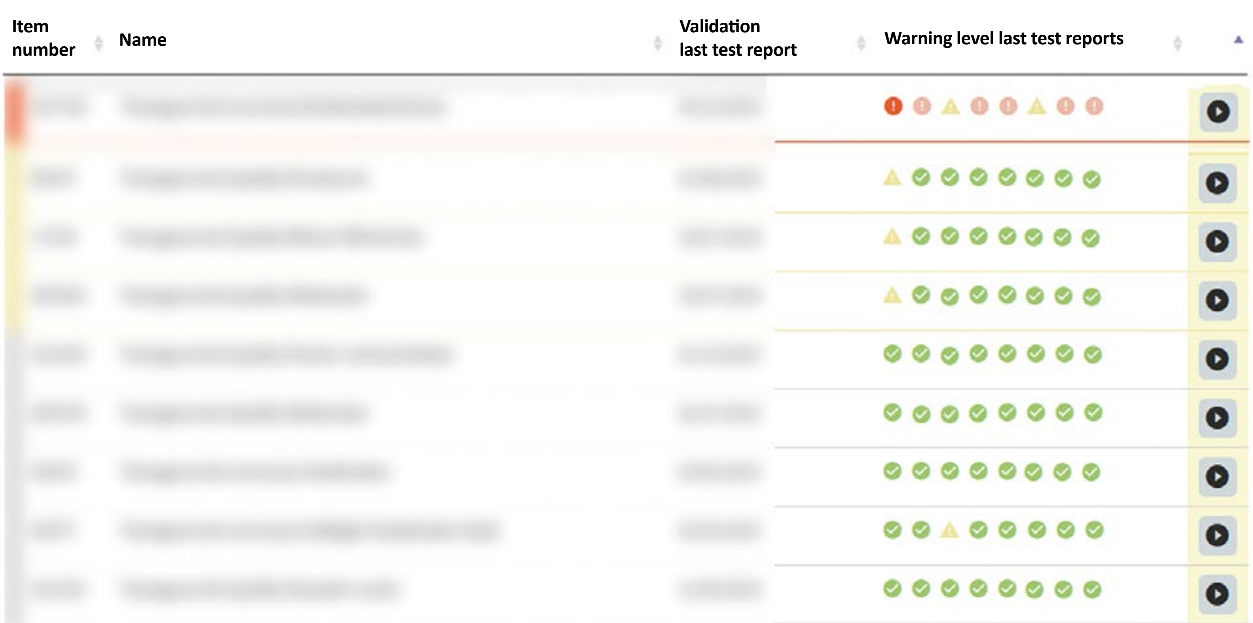


*Figure 6: Case example 3: evaluation of test reports focusing on supplier management (Note: illegible areas in the screenshots are due to data protection reasons)*

It is noticeable here that this supplier's overall profile, which is actually very good, is overshadowed by one individual highly problematic article for which significant BEFFE deficiencies are ascertained in almost every sample. During talks with the supplier, it was determined that the outlier involved an article that was traded on by the supplier but had not been explicitly quality-tested by it. Consequently, the defects were passed on undetected by the supplier, which could have led this otherwise very reliable supplier's being blacklisted if the issue had not been clarified as described above.

The latest test reports for three additional articles on the list simultaneously contain critical comments regarding BEFFE, which was interpreted as an indication of emerging quality erosion. As has already been described above, further analyses are required in such cases of initial suspicion before final conclusions are permitted. In this case, three mutually independent causes of the critical comments were found during audits, which ultimately enabled the initial suspicion of intentional fraud to be discarded.

## Summary with outlook for the value chain

Even the few examples that are thematically limited to one visualisation form and one parameter show that the application of data science and machine learning methods to a company's test report data offers significant potential both in the precise and early identification of suspected cases and in the assignment of company resources in quality management. Particularly compared to the evaluations commonly used today, the machine-supported, systematic shedding of light on the area surrounding the 'dubious quadrant' offers major opportunities for confronting cases of food fraud early on, possibly even in the preparation phase.

The power and the potential of data far exceed the possibilities shown for an individual company in this DLG Expert Knowledge Series text. The food industry has an enormous wealth of data that more or less encompasses the entire 'farm-to-fork' value chain. If the industry were to decide to jointly manage this wealth of data appropriately and to commonly extend the data science/ML toolbox, early warning indicators could already be implemented in earlier process stages and automated using machine learning methods. This would enable the reliable, automated recognition of changing risk situations, and would allow downstream process participants to be warned early on. For example, contaminated raw products could be identified before (potentially several) manufacturers have processed them in their own products, which would significantly reduce risk exposure across the industry. The companies' risk of passing on defects undetected could also be extensively reduced with an overall data management and data analysis system.

While some state-of-the-art data science/ML systems already supplement internal company data with individually compiled environmental data, e.g. from official reporting systems and early warning services, weather services or the like, and therefore make valuable contributions to optimising quality management, the achievable effects will remain limited compared to a cross-company data pool that is fed by as many participants as possible from various stages of the value chain.

The economic advantages that could arise for distributors, for instance, from managing such a cross-company data pool would certainly be substantial: products with comparable risk profiles would not have to be tested individually by each company for the same standard parameters; instead, test plans could be dynamically tightened up with respect to current suspected situations based on automatically generated (anonymised) indications from the common data pool - when 'all is quiet on the BEFFE front' in the network. After it has become known that drug residues have often been mentioned negatively in the test reports of an (anonymised) participant in the network of late, consideration must be given to temporarily shifting internal funds from BEFFE to drug residue analyses - quality managers could therefore make more efficient use of their funds by structuring their test plans dynamically on the basis of evidence.

Unfortunately, the above advantages that are offered by a data pool managed by as many market players as possible are still generating little response in practice. At present, the concept of the networked, common use of data pools with laboratory data, assessments and accompanying information is still encountering reserve. The causes of this are primarily seen in:

- Conflicts of interest between different market players at different stages of the value chain, and
- The widespread concern of exposure by providing internal, sometimes highly sensitive data despite effective anonymisation prior to provision in a data pool.

Implementing the concept of a jointly managed food industry data pool necessitates close cooperation between the disciplines of:

- Product knowledge (guidelines, specifications, etc.),
- Process knowledge (laboratory methods and their limits, manufacturing processes, etc.),
- Data collection, processing and storage (content and technology, IT infrastructure, etc.),
- Data science (feature engineering, model selection and training) and
- Law (food law, data protection law, IT law, etc.).

Overall, it is clear that the creation of a jointly used data pool supported by as many market players as possible for the automated monitoring of neuralgic points in the value chains is still visionary to date: technical and organisational infrastructures are not yet designed for such cooperation as yet, and the interests of potential participants do not match sufficiently in many cases.

However, the use of the first commercially available products and their application to self-control data and analyses of direct upstream suppliers already results in visible increases in transparency as well as specific starting points for systematic quality improvements, together with direct upstream suppliers in some cases.

Therefore, even internal company data is powerful in interaction with data science/ML processes:

- Relief of operational quality and risk management from routine tasks,
- More targeted control of human and financial resources for quality assurance,
- Earlier and more specific options for test plan dynamisation appropriate to the risks,
- Flexible evaluation options with changing information requirements.

Perhaps the likelihood of transforming an industry-wide, jointly managed data pool into reality will also increase as the use of such systems becomes more matter-of-course within companies and the positive effects are felt. Only then would the industry be able to exploit the full potential of the data.

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