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Machine learning in risk models – Characteristics and supervisory priorities

Responses to the consultation paper

Content

I. Feedback from the banking and insurance sector

In July 2021, BaFin and the Bundesbank published the consultation paper entitled "Machine learning in risk models – Characteristics and supervisory priorities" and collected feedback from the insurance and banking sector.

The consultation paper focused on solvency supervision, and specifically the application of machine learning (ML) methods in areas of particular relevance to supervisors. These included, first – as an exception to the principle that algorithms do not require supervisory approval – ML methods that are subject to prudential inspections and approval procedures, i.e. that are used in internal models for calculating regulatory own funds requirements (Pillar 1). Second, ML methods were considered relevant if they are used in risk management under Pillar 2.

The consultation received feedback from associations, including central associations of the banking and insurance industry, as well as from individual insurance corporations, banks, management consultancies and technology companies.

ML has seen hardly any use in Pillar 1 models thus far

The consultation reveals that procedures based on machine learning technologies (ML procedures) are already used in many areas of application at present. According to the feedback, current applications focus on risk management (e.g. money laundering and fraud detection, analyses in credit processes), retail and investment products, product pricing, and individual applications in other risk areas. Thus far, there are only a few instances of ML methods being used in Pillar 1 risk models, although these methods are considered highly promising in some of the responses. ML methods are also used as support or challenger tools.

The following section summarises the responses to the consultation.

II. Characteristics of ML

Broad approval of the 'characteristics approach'

The consultation paper did not develop a universally applicable definition of ML methods, but instead oriented supervisory practice, inspection techniques and inspection intensity around whether and which ML characteristics exist in a specific methodology to be examined and the extent to which they are pronounced. From the perspective of BaFin and the Bundesbank, this differentiation is sufficient for supervisory purposes to assess models under Pillar 1 and Pillar 2.

The characteristics were grouped based on the three dimensions of the **AI/ML scenario:** the **methodology and data basis** collectively describe the complexity and thus the model risk associated with the ML procedure. The **use of the output** contains the importance of the procedure within risk management. The intensity of inspections is not guided by the distinction between in-house development and **outsourcing** or the underlying **IT infrastructure.**

The responses to the consultation reaffirm the approach presented. There is broad consensus that no explicit definition should be prescribed: first, any definition would be insufficient given the wide variety of procedures and their continual further development. Second, no clear distinction can be drawn between ML procedures and traditional ones. Likewise, respondents are in favour of supervisory action being oriented towards the employed procedures in a technology-neutral way. The focus should not be on generalised requirements, but on specific use cases. The AI/ML scenario corresponds to this technology-neutral and case-specific perspective.

In some cases, further possible characteristics were suggested. These include the effects of model deficiencies as well as performance as ML characteristics. Individual responses proposed characteristics that, taken in isolation, cannot be considered specific to ML. These include the data basis, which is characterised more by the availability of data than the method. Other suggestions were automation, adaptivity and complexity, which can sometimes be greater in traditional procedures than in ML.

According to the consultation participants, outsourcing and IT infrastructure should not be considered ML-specific characteristics, neither would they generally form part of the selection and assessment of the ML procedure, nor be subject to their own supervisory framework independent of ML. The feedback shows that no specific risks to IT implementation or outsourcing management arising from ML could be identified, even if the fundamental significance of cloud services and outsourcing is growing with ML.

III. Supervisory approach

1. Supervisory practice endures

The consultation paper explained that Pillar 1 includes extensive regulations for reviewing and approving internal models formulated in a technology-neutral manner and therefore also addresses the risks of ML methods. Principles-based requirements for risk management and IT provide a sound footing in Pillar 2.

The responses to the consultation largely agree that current technology-neutral and risk-oriented regulation also provides a sufficient framework for ML. For Pillar 1 in particular, there is already a comprehensive regulatory framework that could be applied to ML, too. In some cases, the requirements regarding the comprehensibility and measurability of ML procedures are viewed critically.

The supervisory regulatory framework is considered sufficient

Responses from the banking sector assess the ML-related requirements of EBA/GL/2020/06 to be appropriate, technology-neutral, and risk-oriented. Accordingly, no concerns are expressed regarding the implementation and application of regulations to all ML methods in Pillar 2, either.

2. Methods invite to “believe in data”

According to the consultation paper, data quality is already an issue of key importance in supervisory action. Here, however, the characteristics of ML methods make clear that the underlying data should be viewed particularly as a starting point and as a factor for successful outcomes. Unstructured data can now be exploited by and for ML methods. Furthermore, ML methods allow for calculations to be made using a large number of variables, which can, in turn, lead to the problem of “overfitting”. This makes it easy for modellers to quickly apply ML to large datasets. When using large volumes of data, the quality of the data must be ensured on an ongoing basis; in addition to model development and validation, this also applies to model application.

The responses to the consultation unanimously state that all of the data employed must be as representative as possible, and that the use of ML methods would therefore not be grounds for any new or special requirements. The feedback highlights the large amount of manual effort and expertise required for the selection of suitable data: it is becoming more and more important to have an in-depth understanding of the data employed. Insurance companies in particular state that regulatory requirements restrict the volume of usable data, e.g. due to the requirement to focus on just a small number of singular events, or that trends make historical data unsuitable for forecasting. The risk of “believing in data” is reported as already being an issue; participants say that this could be counteracted by high degrees of explainability among the models and/or a wide variety of possible models.

Increased focus on data basis and data quality

The feedback indicates that data quality is already of key significance and should be considered as multifaceted. The responses suggest that software tools (including ML-based tools) could help not only to ensure the quality of the data bases that are already used, but also allow new data sources, such as unstructured data, to be utilised.

3. Focus on explainability

One point of discussion in the consultation paper concerns the explainability of models. As the hypothesis space that can be depicted by the model becomes more complex and more highly dimensional, it also becomes more difficult to describe the functional relationship between input and output verbally or using mathematical formulae, and the details of the calculations are less comprehensible for modellers, users, validators and supervisors. As a result, it is more difficult, if applicable, to verify the validity of the model output as well. User acceptance may also suffer. While this "black box" characteristic may be justified by its higher predictive ability, for example, it leads to potentially greater model risk. In order to take this into account, explainable AI (XAI) methods were developed. In addition, even if XAI methods may seem promising from a supervisory perspective for mitigating the "black box" characteristic, these approaches themselves constitute models with assumptions and weaknesses, and, in many cases, are still in their testing phases.

Explainability is a central criterion in the application of AI/ML

From the perspective of the respondents to the consultation, the reproducibility of calculation results must be ensured; in this context, they believe that the interpretability of model output can be improved using technological means. Explainability should form the basis for selecting the modelling framework. According to the consultation feedback, a vital task of model validation is to check the plausibility of the model, whereby respondents see the complexity of the model as also determining the complexity of the validation. A favourable view is held of models with outputs that are very stable over time and for which jumps in output can be explained by clearly identifiable one-off effects. Validation using appropriate datasets and methods is considered feasible for complex models, too. The majority of respondents believe that not every intermediate step needs to be explainable, but only the final output.

Most of the responses call for the trade-off between performance and explainability to be investigated for each use case. XAI requires such a significant amount of effort to implement that the model's performance must be extraordinarily high in order to justify it. The responses range from "XAI does not fundamentally offer a way out of the black box dilemma" to "XAI solves the black box problem". XAI is not seen as a panacea, as it only investigates selected model characteristics; its use as a basis for expert evaluation is recognised, however. In the opinion of respondents, it is not yet possible to set out supervisory standards for XAI, as the methods continue to develop at a rapid pace.

Costs and benefits of XAI must be reconciled

Respondents believe that downstream XAI can only be implemented on a sample basis. For this reason, they claim that XAI should be a component of validation before the model is brought into operation as well as during ongoing operation. XAI could also serve to identify key variables and thereby construct an almost causal model.

4. Adaptivity: Model changes are more difficult to identify

Institutions and enterprises are obligated to inform supervisors of any changes to Pillar 1 models and, if applicable, only implement these changes after they have been approved. There is no clear-cut distinction between regular model maintenance and model change, which continually leads to discussions with supervisors, especially as the term "model change" is also dependent on the prevailing supervisory context. The consultation paper provided multiple examples of this. However, the flexibility and, in some cases, high-frequency adaptivity of ML procedures can make it more difficult to draw a clear distinction between adjustment and change that would be indispensable for supervisory purposes. As a general rule, the need for high-frequency adaptivity should likewise be thoroughly justified. Even if a large number of ML procedures fall within the supervisory area of Pillar 2 in which approval is not required – and there is thus greater flexibility for retraining and changing the model – existing requirements (e.g. from MaRisk) remain applicable. From a supervisory perspective, it is nevertheless crucial, despite this flexibility, to adapt the training cycle to the specific use case, as well as provide the necessary justification, in order to create a balance between the explainability and validation of the model and ensuring that the data are up-to-date.

The consultation feedback highlights the conflict between model maintenance/calibration and model change, and points out the recurring issue of model drift. Supervisory authorities are requested to further refine the definition of model change as well as generally speed up model approval processes in order to avoid creating competitive disadvantages. Possible definitions and examples for model maintenance and model change are provided: for instance, training a procedure should not be considered model change (neither should the adjustments made to hyperparameters in the process), although the iterative data science process could include trigger points for model change.

Retraining is not observed to exhibit any fundamental particularities; however, depending on data availability, these may need to be clarified in individual cases. According to the feedback, there is no clear boundary between model maintenance and model change in this context, and material changes to the output must be explainable for this reason. The insurance industry in particular does not expect risk models to be retrained more frequently than traditional approaches, although more frequent retraining could be necessary for other areas of application, such as fraud detection. Improving the quality of the model is cited as a reason as to why retraining is required.

Model governance growing in significance; the definition of model change must be refined

With regard to organisational adjustments to the use of ML methods, the responses illustrate the range of vastly different concepts, going as far as merging data science and modelling units. The general consensus is that the separation of modelling and validation should be retained, but the collaboration between the two intensified. Many responses express a desire for clearer model governance.[1]

1 For more information, see also the EBA consultation https://www.eba.europa.eu/eba-consults-machine-learning-internal-ratings-based-models

IV. Outlook

The results of the consultation are the foundation for starting dialogue with enterprises. Alongside the general BDAI principles, this is intended to achieve clarity in the development and application of ML methods in the context of models relevant for supervision in Pillars 1 and 2.

Further discussion is required especially in those areas where the consultation reveals a broad range of opinions, for example with regard to the issues of model explainability and model adaptivity. Certain combinations of characteristics may require more attention from supervisory authorities than others. Supervisors are focused on preserving the ability to monitor risk models.

The ongoing exchange should ensure that there is clarity regarding supervisory expectations and that these expectations are included in the existing Pillar 1 and Pillar 2 frameworks in a technology-neutral way. This will provide enterprises with a regulatory environment that enables them to invest in ML methods and address the risks of these methods as early as possible.

In order to harmonise international approaches as far as possible and establish identical cross-sector criteria for the use of ML methods, the results of the consultation will be incorporated into the implementation of the European Commission's Digital Finance Strategy[2] and discussed with other European supervisory authorities.

2 European Commission (2020), "Digital Finance Strategy for the EU", available online at:
https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0591

Annex – Selected Responses

1. Characteristics of ML

- Do you think it is appropriate to forgo a strict definition of ML methods and instead take an application-based approach and gear supervisory and inspection practice to the individual characteristics of the methods used?

  "We don't consider a strict definition of ML methods to be appropriate."

  "We welcome the suggestion to gear supervisory and inspection practice to the individual characteristics of the methods used. This approach allows us to tier the supervisory and inspection practice between established statistical methods and new ML methods."

  "Owing to the large number of approaches and research groups formed within the ML environment and currently in development, a single definition seems to be unrealistic on the one hand and not that helpful on the other."

  "The strict definition of model characteristics makes no sense, as the ML methods represent only one algorithm for calculating model functions."

- What other characteristics of ML methods do you believe could be important for supervisory practice or for internal model governance?

  "How to deal with open source software, which is increasingly available for ML methods, should be clarified."

  "The model's performance is another important feature. [...] We also consider plausibility to be an important characteristic."

  "We believe reproducibility is a key aspect or characteristic as well, in conjunction with explainability and adaptability."

- In your opinion, which characteristics do not belong in this overview?

  "Data sources and data volumes play only a secondary role for us in differentiating between conventional and modern ML methods."

  "The interpretability of the output is an important point which, in our view, is taken into account in your commentary. It is therefore not necessary to include this as a separate characteristic."

  "Outsourcing processes is a scenario that is generally possible but also already heavily influenced by regulatory requirements. Transparency and governance play a relevant role and this has to be evaluated regardless of whether ML methods are deployed."

- In which relevant areas of application do you employ ML methods or where do you intend to implement them?

  "Some enterprises have already integrated first ML methods as part of validation of the internal model. As far as we know, neither neural networks nor other ML methods are being used yet for official risk capital calculations. [...] These models are already used in distribution and in general operational processes. There are plans to develop elements of the internal risk model further."

  "The actual areas of application are currently limited, although use cases can be found throughout the bank's operations."

  "In many areas we don't see machine learning methods being used at present, but more 'conventional' procedures or (scientific) simulation approaches instead."

  "Currently, ML methods are only used to accompany the development of traditional risk models as challenger models."

2. Supervisory approach

2.1 Supervisory practice endures

- In your opinion, do existing regulations already contain prudential requirements that appear to hinder the use of ML methods? Do you believe that contradictions will arise between prudential regulations for Pillar 1 and 2 models and the draft AI Regulation? Please state any relevant references to the corresponding regulations and explain the challenges.

  "Current inspection and application practice requires a degree of transparency and measurability that does not appear to be available."

  "We share the view of BaFin and the Bundesbank that, owing to its technological neutrality, current regulation and inspection practice already offers an excellent framework for employing ML in risk models."

  "We believe there is no need for concern regarding existing supervisory requirements when using ML methods. The draft AI Regulation is also in line with the regulations for Pillar 1 and Pillar 2 models, and no direct contradictions have been identified."

  "We consider it very important not to hamper the competitiveness of the insurance industry through excessive regulation."

  "Currently, we have not found any regulations that would prevent the use of ML methods in principle."

- To what extent do you believe the requirements laid out in EBA/GL/2020/06 with reference to the use of automated models in creditworthiness assessments and credit decision-making are also suitable for other ML methods in Pillar 2 (MaRisk) and should be taken on?

  "The scale of the relevant requirements laid out in chapter 4.3.4 of EBA/GL/2020/06 for the use of automated models in creditworthiness assessments and credit decision-making have been deemed as appropriate."

"The requirements under EBA/GL/2020/06 with reference to the use of automated models in creditworthiness assessments and credit decision-making should provide a sufficient safeguard. The required measures generally provide a good starting point for applying ML methods in practice."

- Are there any other points where you believe current supervisory practice requires adjustment in order to appropriately acknowledge ML procedures and their associated risks?

  "No."

  "The protection of training, validation and test data as well as the AI application's source code all play an important role in ML processes. [...] Other points that could be relevant to supervisors include a potentially strongly changing data scope, the volatility of the output and a lack of documentation on algorithms."

  "We do not believe that there are any other points where existing supervisory practice requires adjustment."

  "We consider this to have been covered by training/expertise/standards and directives."

- Do ML methods entail specific risks for IT implementation and outsourcing management? Are "adversarial attacks" conceivable in the financial sector and should ML methods be given particular protection against such attacks?

  "From the perspective of numerical analysis, the implementation of ML algorithms has a strong analogy to previously used methods, meaning that there is no need to reclassify any other specific IT risks besides the aforementioned data protection topic (existing risks may need to be adjusted if necessary)."

  "We see no risks specific to ML for IT implementation. The current requirements already apply to conventional ML models. [...] Adversarial attacks are generally possible on all ML systems. The degree of protection is derived from the sensitivity of the data represented in the model and the relevance of the processes supported by the ML system."

  "As the group of people with access to the data streams relevant to risk calculation is generally limited and clearly defined, and a large number of controls and checks have been set up, we do not consider there to be a greater risk from adversarial attacks. Furthermore, and regardless of the methods used, the significance of IT risks is growing due to the rise in data exchange and processing."

2.2 Methods invite to „believe in data“

- What challenges do you see when selecting data and when ensuring data quality with regard to ML methods?

  “Data credibility is not just a phenomenon for ML/AI but also exists in the conventional environment.”

  “The requirements for data quality are not specific to certain methods and have already been addressed previously in model development processes. Data modellers’ expertise and experience are crucial when selecting data and ensuring data quality, especially for complex models. We do not believe ML methods simplify the selection and quality of data.”

  “It is important that the datasets used match the real data as far as possible to ensure that they remain representative for the “use case”. The more that data are anonymised (primarily for data protection reasons), the further datasets and the models trained on them become removed from the real data, which may lead to modified ML models and additional risks.”

  “The possibility of using unedited raw data in many ML methods and the efforts of many institutions to automate processes across all areas may tempt them to include variables in models without any manual interaction regardless of the underlying data quality or – even more worryingly – without checking the meaningfulness of the variables to the underlying problem.”

  “When using methods subject to strict data protection, such as machine learning, critical questions should be asked as to whether the data are actually suitable for extrapolating scenarios relevant for capital requirements.”

- In your opinion, what aspects of data quality are made easier through the application of ML methods?

  “Quality assurance and data protection are already in focus.”

  “We consider it advantageous if many data (including metadata) are used for AI/ML, as they can strengthen the robustness of ML models. ML methods can be used to intelligently replace missing datasets and thereby improve the model’s quality.”

  “The broader the dataset used, the lower the model’s expected loss of performance should a feature/data source ’fail’.”

  “ML methods are capable of identifying disturbances or distortions in the data to a certain extent and of calculating meaningful output even when the data are incomplete or disrupted. Nevertheless, the data preparation process prior to the actual process of developing the model is extremely important, requiring a consistently high level of quality.”

2.3 Focus on explainability

- In your opinion, what impact does the black box characteristic have on the validation of the procedure?

  "The black box characteristic is based on the model's high level of complexity, meaning that causality relationships cannot be shown transparently. However, we assume that a result which is reproducible rather than driven by randomness must be guaranteed going forward when using ML methods. The interpretability of the output can be improved through suitable methods (e.g. a sensitivity analysis)."

  "For good reason, pure black box models that do not attain at least a basic level of explainability using XAI techniques should never be used, especially in the context of risk models."

  "As long as the model output is also stable and verifiable over time, and one-off effects (temporal and technical) have been sufficiently trialled, the black box characteristic is viewed as unproblematic."

  "The "black box concept" is not correct in this respect. We believe a better image would be a complex clock mechanism in which it is only clear which cog is touching which, but the entire mechanism and the interactions within it cannot be readily understood. In a similar manner, an ML model can be approximated locally by using a simple linear model. The validation of the black box characteristic can be made easier by using XAI approaches."

  "The effect of the black box characteristic on validation should be borne in mind for each individual case."

  "ML/AI-based output or the suitability of methods have to be explainable or plausible for specialists but not every individual operation or individual interim results. Even conventionally produced statistics are not meaningful when viewed in isolation, their output and methods have to be interpreted first."

  "When using modern ML methods, the process of making the black box explainable (opening the black box) should be both part of the initial validation process directly after the model has been developed and part of the regular validation process while the model is up and running."

- How important is the trade-off between performance and explainability for you?

  "Depending on the use case, either the explainability or the performance of the model can be deemed more important. The real challenge lies in adapting the complexity in the ML method to the complexity of the problem. We don't see a trade-off between explainability and performance."

  "Weighing up performance and explainability is always a good idea when selecting a model irrespective of whether it is an ML model or a conventional model."

  "The trade-off between performance and explainability is very important to practice and this has to be weighed up depending on the application."

- Do you believe XAI methods (always) offer a way out of the black box dilemma? Which processes are the most promising and for which ML methods?

  "As XAI techniques can indeed require considerable effort to validate conventional models in practice, this effort should be offset by a significant gain in performance."

  "In our view, XAI techniques are not a way out of the black box. Various XAI techniques can only highlight those features that were primarily crucial to a prediction."

  "XAI techniques are suitable tools for enhancing the interpretation of models."

  "It remains for experience to show which methods are best suited to assessing the behaviour of algorithms. The development of other methods to analyse algorithms' behaviour is a dynamic area currently – especially for algorithms from the BDAI area. Accordingly, we believe it is too early to look at setting standards for this area."

  "Every approach harbours the risk of trusting the output too readily. In any case, focusing on models and input data as well as intensively verifying the output of XAI methods will be essential."

- How do you think an XAI integrated downstream of the method should be incorporated into the validation process?

  "A downstream XAI can be used to check whether a model's decision was correct. [...] This is just a manual check that could be employed at random in order to document that a certain quality has been attained."

  "The regular application of XAI techniques is recommended in order to understand the ML models better. XAI techniques can be included both during development and as an ex post tool."

2.4 Adaptivity: model changes are more difficult to identify

- What questions on supervisory practice do you see arising with regard to model adjustments for ML methods?

  "Updating the data or changing the (hyper)parameters that result solely from training the model in ML models do not constitute a model adjustment as these instead represent components of applying the model under the current market/business conditions."

  "Even previously, a new calibration, provided that it met the established quality standards, did not necessarily constitute a model change. It would therefore be reasonable to state that there is no model change for ML methods either, provided that they meet certain quality standards. This too, of course, depends on the application."

  "The existing regulatory framework and model approval are sufficient; they do not require extension. Banks guarantee certain aspects through their individual governance."

  "Supervisors should outline clear criteria to delineate model maintenance from model changes subject to approval."

  "Training (including tuning hyperparameters) is a regular process and should not be classified as a model change subject to supervisory regulations. It is part of the (annual) recalibration."

"Shouldn't changes in the weights of the information types used rather than changes to the risk factors used be considered when distinguishing model maintenance from model changes? Switching a feature should not necessarily be recorded as a model change if the new feature provides very similar information."

- Do you believe it is necessary for certain ML methods to be retrained at very high frequencies?

  "Regular model retraining is considered useful regardless of the methodology chosen, i.e. even in the case of conventional regression models."

  "It should also be borne in mind that "data science" consists of iterative cycles. The question arises as to the point at which a cycle is considered completed, and when a new one begins. This could then be a trigger point for a model adjustment by the supervisory body. We believe that retraining at very high frequencies is not required. The driving force behind changes to model output tends to be the underlying data and their volatility/expansion."

  "The models are recalibrated regularly, meaning that the distinction between model maintenance and a model change subject to supervisory assessment is already relevant nowadays. The necessity of frequent retraining strongly depends on the use case in question. It should not be more frequent than for existing models. Furthermore, model changes for ML methods should not focus solely on individual parameters, meta parameters or the model's output, but on the learning process in its entirety, including all meta parameters, i.e. optimisation across various modelling approaches should be viewed as part of the learning process. Only when a learning process has been modified should it be classified as a model change."

  "As such, retraining is only carried out when a higher level of quality is expected as a result. Retraining is not continued if the retrained model does not show a higher quality level."

  "For Pillar 1 and Pillar 2 applications, we believe that retraining would not be necessary that often under normal circumstances (unlike applications that include customer service, for example)."

  "For methods in particular that require retraining the models frequently, we believe it is important to ensure that this does not produce any major jumps in the output variables. If jumps do occur, this should be identifiable and justifiable in the model monitoring."

- Do you see ML methods necessitating changes in model governance?

  "Due to the technological neutrality of the regulations and supervisory practice, the use of ML methods in internal models does not generally require changes to the supervisory approach."

  "In model governance such as this, all parties are involved, as the entire process from data load to model deployment has to be explained and documented so that each party can understand what is input for the model and what output it provides."

  "Model governance can remain unchanged."

  "We believe that ML methods will cause pre-existing aspects of model governance to become more clearly apparent than before."

- How do traditional modelling units, validators and new "data science" units work together?

  "The purpose of the validation function is to perform an independent review of the models, processes and calculations. This should also include reviewing the current methodology. ML methods can be used by both modelling units and validation units. Ideally, there should be a lively exchange between these two units, and this may also include other "data science" units (if these have already been implemented)."

  "The time-tested division of labour between modelling and validation should be maintained. We do not consider it necessary to made adjustments. That said, traditional modelling units should not work separately from new "data science" units. Generally, a common understanding of the new methods should be cultivated on the development and validation side."

  "Data science and modelling units will merge with one another when an ML model is used productively, while validators will continue to act independently as before. It is conceivable that knowhow for successful validation will increasingly be transferred via the data science unit."

  "Regardless of the ML methods, close cooperation between modelling units and validation units is recommended. The validation unit should constructively review the appropriateness of the developed models, processes and output. [...] "Data science" is a new field for some insurance companies, which means that their own "data science" teams may not necessarily be firmly anchored yet. In any case, there should be a regular exchange of views between all departments regarding best practices and areas of application (e.g. as part of "use cases")."

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