German Banking Industry Committee

Die Deutsche Kreditwirtschaft

Position Paper

Key Considerations for the Implementation of the AI Act with regard to the Definition of an AI System under Article 3(1) AI Act by the German Financial and Insurance Industry

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The **German Banking Industry Committee** is the joint committee operated by the central associations of the German banking industry. These associations are the Bundesverband der Deutschen Volksbanken und Raiffeisenbanken (BVR), for the cooperative banks, the Bundesverband deutscher Banken (BdB), for the private commercial banks, the Bundesverband Öffentlicher Banken Deutschlands (VÖB), for the public-sector banks, the Deutscher Sparkassen- und Giroverband (DSGV), for the savings banks finance group, and the Verband deutscher Pfandbriefbanken (vdp), for the Pfandbrief banks.

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Article 3(1) AI Act by the German Financial and Insurance Industry

On behalf of the German financial and insurance industry, which represents around 2,500 companies from the traditional financial sector, we are reaching out on a matter that is critical for the implementation of the EU AI Act. We are concerned by indications that, at this critical stage, the EU AI Office may be reconsidering its previous interpretation of the definition of an "AI system" and may possibly extend it to common statistical methods. Such a reinterpretation would run counter to the regulatory purpose and the overall structure of the AI Act, significantly impair legal certainty and weaken regulatory credibility. As a result, there is a risk of significant disadvantages for the competitiveness of the European financial and insurance market.

Especially at a time when the Commission is explicitly prioritizing competitiveness, simplification and the reduction of regulatory burdens, such a reinterpretation would directly run counter to these central objectives and at the same time send a negative signal to investors and market participants.

We therefore advocate a reliable and coherent digital regulatory framework that strengthens innovation and trust in equal measure. Clear legal frameworks are required for the safe use of AI in the financial and insurance sector, as well as a consistent focus on simplification and better regulation in order to ensure the proportionality and practical applicability of EU rules on a lasting basis.

Distinguishing AI Systems from Conventional Software Systems

The definition of AI set out in Article 3(1) will be of decisive importance for the future scope of the AI Act. The German insurance and banking industries therefore welcomed the fact that the guidelines on the definition of an AI system presented by the European Commission in February 2025 explicitly clarified that a number of well-established methods and systems (including linear and logistic regression methods) do not fall under the AI definition and are therefore excluded from the scope of the AI Act. The Commission's guidelines make clear that such methods, for example linear and logistic regression, do not constitute inference going beyond "basic data processing", but are to be understood as mathematical optimization methods that are explicitly "out of scope".
The current uncertainties do not concern the interpretation set out in the guidelines as such, but rather the question of its continuing validity and practical reliability.

In light of the recent uncertainties and interpretative difficulties of some national supervisory authorities, further clarification is required. The decisive factor for classification as an AI system should not be the use of individual mathematical or statistical methods, but solely the way a system functions as a whole. What matters is whether the decision-shaping logic of a system is materially influenced—and not merely supported or prepared—by adaptive, data-driven or not fully traceable mechanisms.

Stand-alone Regression Models Are Not AI Systems

Stand-alone regression models should generally not be classified as AI systems within the meaning of the AI Act, since they lack the features relevant to the AI definition (in particular adaptive, data-driven or not fully traceable inference mechanisms): The model structure is fully specified, the effect of individual variables can be determined parametrically and unambiguously, and the results are fully traceable and reproducible. Decision-making takes place within a framework defined by human modelling. Regression models therefore exhibit neither the opacity nor the functional complexity or adaptive self-dynamics that are characteristic of AI systems.

This not only creates a clear distinction from simple and conventional software systems and programming approaches that are based exclusively on rules defined by natural persons for the automatic execution of operations. It also underscores the need for a differentiated classification between rule-based software, statistical methods and genuinely AI-based systems.

The following examples of software systems or programming approaches from the insurance and banking sectors exemplify transparent, non-adaptive methods that accordingly do not fall under the AI definition:

- Classical expert systems that may, for example, be used in health insurance. These are essentially rule sets that assess a specific case. The results are always the same in accordance with the predefined rules. The system does not undergo any automatic further development.
- Generalized Linear Models (GLMs), which differ from AI in terms of their complexity and autonomy. These require human intervention in data selection, model selection and the interpretation of results. Moreover, these models are not so-called “black boxes”, since the influence of the features on the model outcome can be determined transparently on the basis of the model parameters.
- Logistic regression as a special case of generalized linear models. It is likewise characterized by low complexity and, at the same time, high interpretability. As a result, with logistic regression the risk of unexpected behaviour is significantly lower than, for example, in neural networks.
- Traditional credit-scoring and rating models in the banking sector that are based on logistic regression approaches or comparable statistical methods: These models are based on professionally curated, stable features (e.g. income, debt ratio, payment history), are structured in a linear-additive manner and are designed for consistency and long-term comparability. They serve as a transparent mapping mechanism for deriving probabilities of default and are fully traceable and auditable.

These methods are also embedded in comprehensive model-governance and validation frameworks. Banks and insurance companies implement standardized processes throughout the entire model life cycle, from model development through independent validation and approval to ongoing monitoring, change control and regular revalidation.

These frameworks include, in particular:

- an independent review of model design, data basis and performance,
- documented model assumptions and specifications,
- versioning and change processes (change management),
- regular back testing and stability analyses, and
- full traceability of model decisions (audit trail).

This ensures that logistic regression models are at all times reproducible, explainable and capable of supervisory review. These properties stand in clear contrast to the typical characteristics of complex AI systems.
An extension of the AI definition to established statistical methods would, moreover, lead to significant overlaps with existing European supervisory frameworks, in particular the requirements on governance, risk management, documentation, validation and operational resilience applicable in the financial and insurance sectors, including Digital Operational Resilience Act. To the extent that transparent, stand-alone logistic regression models are already embedded in such control and governance frameworks, their parallel inclusion under the AI ACT would result in duplicate regulation and increased regulatory complexity, without necessarily providing a corresponding risk-based added value.

This differentiated treatment is also supported by the scientific literature, which consistently treats logistic regression as an inherently interpretable benchmark model, in contrast to more complex machine-learning techniques that raise additional explainability concerns.[1]

Regression Models in Multi-stage System Architectures

At the same time, statistical methods—including logistic regression—can be used in different operational contexts, for example as part of more complex data and model architectures (e.g. as a final estimator within a model pipeline). In such cases, a differentiated function-based assessment is required:

Logistic regression can play a dual role in this context. Its mathematical structure remains unchanged in both cases. The difference lies in the systemic embedding: In classical use cases, especially in banking and insurance, logistic regression is part of a fixed risk logic based on stable variables, is traceable and involves no autonomous adjustment. In data-driven architectures, by contrast, it can form part of a learning risk logic in which models are regularly retrained, features are dynamically generated or transformed, and additional methods shape the decision-making process. In such cases, the regression model is part of an adaptive overall system.

[1] See, Alonso and Carbó, *Accuracy of Explanations of Machine Learning Models for Credit Decisions* (Banco de España Working Paper No. 2222, 2022); Majumdar, *The Accuracy-Interpretability Dilemma* (2025); Schwartz, Wang and Fang, *Enhancing ML Interpretability for Credit Scoring* (2025); Bussmann et al., *Explainable Machine Learning in Credit Risk Management* (2021); Molnar, *Interpretable Machine Learning* (2019/2022 ed.); Rida, *Machine and Deep Learning for Credit Scoring: A compliant approach* (2019); Yeo et al., *A comprehensive review on financial explainable AI* (2025).

The decisive difference therefore lies not in the method ("regression") as such, but in whether the model is part of a stable, traceable decision logic or embedded in a dynamic, data-driven system architecture that materially shapes decision-making. "Decision-shaping logic" exists in particular where methods

- influence the selection or generation of features in a way that is material to the model decision and is not fully determined by fixed, predefined rules,
- dynamically or data-drivenly alter the weighting, transformation or combination of variables and thereby shape the model's behaviour, or
- use adaptive, non-deterministic or continuously learning mechanisms that modify the decision logic over time.

Conversely, no decision-shaping function exists where methods merely perform supporting or preparatory tasks without materially influencing the final decision logic and where their effect remains fully traceable and reproducible.

Against this backdrop, the mere integration of a transparent statistical method into a multi-stage processing chain does not in itself justify classification as an AI system. What is decisive is an overall functional assessment of the system architecture and, in particular, whether upstream or downstream components substantially shape the decision logic of the overall system. Accordingly, classification as an AI system should only be considered where such methods are embedded in a system context in which other components materially shape the decision logic, in particular through adaptive or not fully deterministic mechanisms.

Economic Impacts as well as Scaling and Broad-based Effects of the Interpretation

Including logistic regressions and other established statistical methods within the scope of the AI Act would not only have significant negative effects on the competitiveness of the European banking and insurance sector, but would also have structural effects on costs and market structure. For decades, these methods have formed the basis of stable, transparent and well-understood business models and are central to efficient and reliable processes.

The economic effects of an overly broad AI definition arise in particular from the threatened blanket capture of low-risk standard methods, the regulation of which would be neither proportionate nor appropriate.

Investment, development and compliance decisions in the European banking and insurance sector have so far been based on the interpretation of the AI definition in accordance with the Commission's guidelines of February 2025. A subsequent extension of the scope of application to established statistical methods would substantially alter these planning assumptions, impair investment and legal certainty, and weaken companies' ability to implement innovations efficiently.

Given the widespread and standard use of statistical methods, the interpretation of the AI definition has considerable scaling and broad-based effects. An undifferentiated inclusion would direct implementation and supervisory resources toward applications without specific AI risk while simultaneously diverting resources away from AI systems that are actually risk-relevant—with corresponding adverse consequences for the EU's competitiveness.

Our Request

To avoid room for conflicting interpretations, the Commission should clarify the following:

The use of traditional statistical methods in stand-alone applications does not result in classification as artificial intelligence within the meaning of the AI definition under Article 3(1) AI Act. This applies in particular to methods that do not exhibit any form of machine learning or self-optimization. This includes, especially, linear models, Generalized Linear Models (GLMs), logistic regression and comparable established statistical methods, provided they are used as stand-alone models and their decision logic is fully traceable and reproducible.

Only a precise, consistent and feasible interpretation ensures that the AI Act is applied in a targeted manner to systems that are actually risk-relevant, without at the same time subjecting proven, transparent and fully controllable methods to disproportionate regulation.
Against this background, a timely and transparently comprehensible confirmation of the previous interpretation is required, according to which long-established statistical methods continue not to fall within the scope of the AI Act. Such a stable, predictable and proportionate regulatory framework is essential both for the effective implementation of the AI Act and for fostering investment and innovation in Europe.

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