DAV
Deutsche
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*Statement of the German Association of Actuaries (DAV)*

# DAV Calls for Legal Clarification: Classical Statistical Methods Should Be Distinguished from AI Systems under the AI Act

Cologne, 8 June 2026

**Executive summary:** Classical statistical methods used in actuarial practice are transparent, human-controlled, and non-self-adapting. They should therefore not be treated like AI systems under the AI Act. A clear distinction would increase legal certainty, avoid unnecessary compliance burden, and help supervisors focus on genuinely risk-prone AI systems, creating room for responsible innovation and faster adoption in the European insurance industry.

## 1. Background and Position of the DAV

With Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (hereinafter: AI Act), the European Union has for the first time created a horizontal legal framework for AI systems. The European Commission's guidelines on the definition of an AI system, set out in Communication C(2025) 5053 final of 29 July 2025, are intended to give guidance for the practical interpretation of Article 3(1) of the AI Act. From an actuarial perspective, however, considerable scope for interpretation remains open, in particular for classical statistical methods such as linear and logistic regression as special cases of generalised linear models (GLMs), and GLMs as special cases of generalised additive models (GAMs). These methods have formed part of the standard methodological repertoire of actuarial science for three decades and have proven their worth over the long term, for example in decision-relevant applications such as pricing or risk assessment. Actuaries are trained over many years in their application and thereby ensure traceability, transparency, and non-discriminatory use.

The German Association of Actuaries (Deutsche Aktuarvereinigung e. V. – DAV) takes this scope for interpretation as an occasion to set out its professional position: classical statistical methods should not be classified as AI systems within the meaning of Article 3(1) of the AI Act. This statement explains why this distinction follows from the legal criteria themselves and asks the European Commission to provide explicit clarification.

## 2. Legal Framework: The European AI Act

Decisive for the question to be assessed here is the definition in Article 3(1) of Regulation (EU) 2024/1689. It reads:

> *"[An] AI system [is] a machine-based system that is designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments."*

Within this definition, the Commission guidelines distinguish seven main elements. For the delineation question at hand, four sets of characteristics in particular can be derived from the above definition: (i) the machine-based character, (ii) the design to operate with varying levels of autonomy, (iii) possible adaptiveness after deployment, and (iv) the capability to infer, from the input received, outputs for explicit or implicit objectives. While the machine-based character is generally given owing to the analysis of large volumes of data, the characteristics of autonomy, adaptiveness, and inference capability are particularly decisive for the delineation of classical statistical methods.

Recital 12 of the AI Act gives concrete form in particular to the characteristics of inference and adaptiveness. It clarifies that the capability of an AI system to infer "transcends basic data processing" and enables learning, reasoning, or modelling. An AI system is adaptive if it possesses a self-learning capability through which it can "change while in use".

## 3. Actuarial Assessment of the Defining Elements

The DAV undertakes its assessment along the three characteristics of Article 3(1) of the AI Act that are particularly decisive for classical statistical methods: autonomy, adaptiveness, and the capability to infer. Additionally, several professional indicators are used as evidence. These include professional pre-specification, a limited and structurally transparent solution space, the lack of autonomous changes to the model structure, and methodological traceability. From an actuarial perspective, these indicators argue against classifying classical statistical methods as AI systems. This applies in particular to (multiple) linear and logistic regression as a special case of GLMs, GLM and GAM applications, Cox proportional hazards models, and statistical structure-analysis methods such as clustering or principal component analysis. Their model structure and parameters are not changed autonomously during operation, but are professionally specified, selected, and validated by actuaries or other responsible expert functions.

This statement does not pursue an exhaustive enumeration of individual methods, but rather a principles-based delineation based on the defining elements of Article 3(1) of the AI Act. The following considerations proceed by way of example based on classical GLM and GAM applications. The delineation criteria presented are in principle also relevant for comparable, non-self-adapting statistical modelling and analysis methods.

### a) Autonomous Operation

In actuarial practice, statistical models are regularly used in automated form in operational processes – in the sense of an unattended program run – for example in pricing in property and casualty insurance or in risk assessment in health and life insurance. This operational automation must, however, be distinguished from AI-typical autonomy, in which the system acts with "some degree of independence of actions from human involvement", infers from inputs how outputs are generated and, in doing so, goes beyond the mere execution of fully predefined computational rules.

In classical statistical models, the entire solution space is described by a model equation. This equation – consisting of target variables, explanatory variables, their interactions, and model parameters – is specified and maintained by subject-matter experts, for example from the actuarial function, product development, underwriting, and insurance medicine. The system makes no decisions that are not laid out in advance in the model equation. Updates are carried out exclusively by the professionally responsible persons, for example in the event of advances in medical knowledge or of changes in the portfolio profile and pass through the established validation and approval processes. There is therefore no independent modification of the decision logic by the system.

### b) Adaptiveness after Deployment

In their customary actuarial design, classical statistical methods do not self-adapt during ongoing operation. For example, the model equation of a GLM or GAM, once estimated, remains unchanged between regular model updates; newly incoming data influence the model output exclusively via the explanatory variables provided for in the model equation, not through any independent change to the structure or the underlying parameters.

Model updates are a human-controlled process comprising a renewed specification, a new statistical estimation based on deliberately selected data, comprehensive model validation, and a professional plausibility check. They are embedded in the supervisory governance of insurance undertakings, in particular the governance requirements under Solvency II, the relevant requirements of the German

Federal Financial Supervisory Authority (BaFin), and the professional standards of the DAV. Structurally, this distinguishes classical statistical methods from self-learning machine learning methods whose decision logic can evolve autonomously while in use and which exhibit the "self-learning capabilities" referred to in recital 12. The absence of self-adaptation is thus a key indication against AI-typical adaptiveness within the meaning of the AI Act.

### c) Inference Capability, Solution Space, and Explainability

For GLMs and GAMs, the solution space is predetermined by the model equation. Every output results reproducibly from applying this equation to the input values; the effect of the model parameters is interpretable in principle, their marginal effects can be read off, and sensitivities are methodologically traceable.

Recital 12 of the AI Act requires of an AI system a capability to infer that "transcends basic data processing" and takes place through learning, reasoning, or modelling. From an actuarial perspective, properties such as the structurally limited solution space, reproducible and methodologically traceable model outputs, and parametric or methodological explainability argue against such a relevant, qualified capability to infer. Accordingly, GLMs and GAMs, which in their classical actuarial design regularly exhibit these properties structurally, should not be classified as AI systems within the meaning of Article 3(1) of the AI Act.

| Definition of an AI system under Article 3(1) of the AI Act | GLM / GAM |
|---|---|
| (1) A machine-based system | ✓ |
| (2) that is designed to operate with varying levels of autonomy | ✗<br>*The model equation, consisting of target variables, explanatory variables, their interactions, and model parameters, is fully specified and maintained by professionally responsible persons.* |
| (3) and that may exhibit adaptiveness after deployment | ✗<br>*No self-adaptation takes place; model updates are a human-controlled process.* |
| (4) and that, for explicit or implicit objectives, | ✓ |
| (5) infers, from the input it receives, | ✗<br>*The solution space is predetermined by the model equation. Owing to the absence of self-adaptation during operation and to parametric explainability, all outputs are reproducible and methodologically traceable.* |
| (6) how to generate outputs such as predictions, content, recommendations, or decisions | ✓ |
| (7) that can influence physical or virtual environments. | ✓ |

## 4. Why a Broad AI Definition is a Risk for Actuarial Practice

A blanket subsumption of classical statistical methods, which have been applied reliably in insurance for decades, under Article 3(1) of the AI Act would have considerable consequences for actuarial practice that are not justified on the merits. It would lead to double regulation alongside the existing actuarial and supervisory governance of these methods – in particular the requirements under Solvency II, the Insurance Distribution Directive (IDD), the BaFin requirements, and the professional standards of the DAV – without any discernible additional contribution to consumer protection, to the benefit of the collective of insured persons, or to the protection of the fundamental rights of policyholders and other affected persons.

It would, moreover, create an adverse steering effect, because it would move transparent and parametrically explainable models, in regulatory terms, closer to more complex, less interpretable model architectures without this being justified by a comparable risk profile. Consequently, in decision-relevant applications – for example in pricing, risk assessment, or acceptance decisions – the incentive to rely on methodologically clear and traceable methods could decline. If transparent models were subject to largely the same requirements as complex AI methods, this could favour the choice of more complex approaches. These, however, regularly feature lower transparency, traceability, and freedom from discrimination. The result would be a shift away from methodological clarity, which is precisely what the legislator does not intend.

A broad definition would also make it harder to distinguish transparent and controllable statistical methods from genuinely risk-prone AI systems, including generative AI and large language models. Supervisory attention and compliance resources should focus on systems that are difficult to scrutinise from the outside, not on methods that are already transparent, human-controlled, and methodologically traceable.

## 5. Positioning in the European Regulatory Discourse

The position of the DAV set out here is in line with converging statements by other European institutions. The Chairperson of EIOPA, in a letter to the European institutions, has suggested removing GLMs, linear and logistic regression, and GAMs from the scope of high-risk AI. The European Central Bank, in its Opinion CON/2026/10, has put forward a similarly directed line of argument for the financial services sector. The European Commission’s guidelines give concrete form to the reach of the concept of AI as regards classical statistical methods and cite linear and logistic regression as examples of methods which, despite elements of inference, may fall outside the definition of an AI system. From an actuarial perspective, this classification is to be welcomed; however, it should also capture GLMs and GAMs, as well as comparable statistical methods with the structural characteristics set out in Section 3, as methodological generalisations. Since the guidelines are not legally binding and the Commission moreover refers to case-by-case assessment, a grey area remains, which the DAV assesses independently based on the characteristics developed in this statement.

The German Insurance Association (GDV) likewise calls for a corresponding clarification already at the definitional level of the AI Act. The Actuarial Association of Europe (AAE) points to the decades of reliable application of these methods in actuarial science. With a view to innovative capacity and practicability, BaFin also advocates a definition of AI systems that is narrower and as pragmatic as possible.

The DAV bases its position independently on the professional reasoning developed in Section 4 and regards the statements referred to as a point of convergence in the European discourse.

## 6. What the DAV Calls on the European Commission to Clarify

Based on the foregoing assessment, the DAV sees a need, in the interests of clear and proportionate regulation, for three specific clarifications:

*The DAV calls on the European Commission to clarify explicitly that classical statistical methods should generally not be classified as AI systems under Article 3(1) of Regulation (EU) 2024/1689 where they are transparent, professionally pre-specified, and non-self-adapting. This includes, in particular, linear and logistic regression as special cases of GLMs, GLM and GAM applications, and comparable statistical methods with the structural characteristics set out in Section 3.*

*The DAV calls for this clarification to explicitly take into account the delineation indicators set out in Section 3 that are decisive from an actuarial perspective: a limited and structurally transparent solution space, the absence of autonomous self-adaptation, and parametric or methodological explainability. These criteria permit an appropriate delineation of classical statistical methods from AI systems within the meaning of Article 3(1) of the AI Act and at the same time give effect to the distinction laid down in recital 12 between basic data processing and a qualified capability to infer.*

The DAV offers policymakers a professional exchange on this delineation and emphasises that the existing actuarial and supervisory governance of classical statistical methods is appropriate and sufficient to address the specific risks of these model classes, while AI-specific requirements should focus on systems with genuinely AI-specific risk profiles.

## Annex: Illustration of the Differences Between a GLM and a Neural Network Using the Example of Motor Insurance Pricing

The delineation criteria referred to in Section 3 can be illustrated using a simplified actuarial example A GLM for estimating claim frequency, as required for the pricing of motor insurance, uses a model equation that is predefined by experts and consists of a target variable, explanatory variables, their interactions, and model parameters. The solution space of this equation is described fully parametrically, marginal effects can be read off, and the model's response to a change in the input data can be documented in a traceable manner, as the example specification below shows.

By contrast, with neural networks, a complex method of the machine learning type, the prediction of claim frequency generally takes place via a multitude of model-internal transformations with a high number of parameters. The influence of individual features frequently cannot be derived directly from the model equation and requires additional explainability and validation measures.

Both methods are based on a relationship between age, annual mileage, regional class, type class, and claim frequency that is predefined by experts. The data used were generated exclusively for illustrative purposes and are not intended to represent a real insurance portfolio. The number of claims per policy $i$, denoted $N_i$, is modelled as Poisson-distributed with expected value $\mu_i$; the natural logarithm serves as the link function.

$$log(\mu_i) = \eta_i = \beta_0 + \beta_1 \cdot Age_i + \beta_2 \cdot Mileage_i + \beta_3 \cdot Regional\_class_i + \beta_4 \cdot Type\_class_i$$

$$E[N_i] = \mu_i = exp(\eta_i)$$

The following table shows an illustrative parameterisation of the model. The values are chosen so that the qualitative effects of typical rating factors become apparent; they are no substitute for a company-specific estimation on a real portfolio. The model equation, including the variables used and the functional relationships, is professionally defined and remains unchanged during operation. Newly incoming data influence the model output exclusively via the variables provided for and the estimated model parameters, but not via any autonomous change to the equation itself.

| Parameter | Estimate | Interpretation |
|---|---|---|
| $\beta_0$ (Intercept) | −3.50 | Level of the log claim frequency in the reference case |
| $\beta_1$ (Age) | −0.025 | Decrease in frequency with age |
| $\beta_2$ (Mileage) | $+4.5 \cdot 10^{-5}$ | Increase in frequency with annual mileage |
| $\beta_3$ (Regional_class) | +0.180 | Effect of a higher regional class |
| $\beta_4$ (Type_class) | +0.140 | Effect of a higher type class |

The model output is reproducible and traceable: every combination of input values yields a unique expected value of the claim frequency. The effects of individual features are parametrically and methodologically explainable from the model structure; sensitivity and outlier analyses are methodologically well established.

The figure below contrasts the solution space specified by the GLM with that of an exemplary neural network on the identical data basis. While the GLM in the left panel exhibits a smooth, structurally traceable, and parametrically describable solution space with professionally interpretable and plausibility-checkable relationships between the age of policyholder and the claim frequency, the neural network in the right panel shows a considerably more complex and less transparent solution space with structures that are in places locally irregular and non-monotonic. The relationships in the GLM remain methodologically traceable by means of established actuarial-statistical procedures, whereas the internal representation in the neural network takes place via a multitude of hidden parameters and activation functions and thus largely eludes direct interpretation.

The properties presented here are not incidental features of this example, but structural properties of the GLM model class and – with additive smoothing – also of the GAM model class. They substantiate the delineation of these methods from AI systems within the meaning of Article 3(1) of Regulation (EU) 2024/1689.

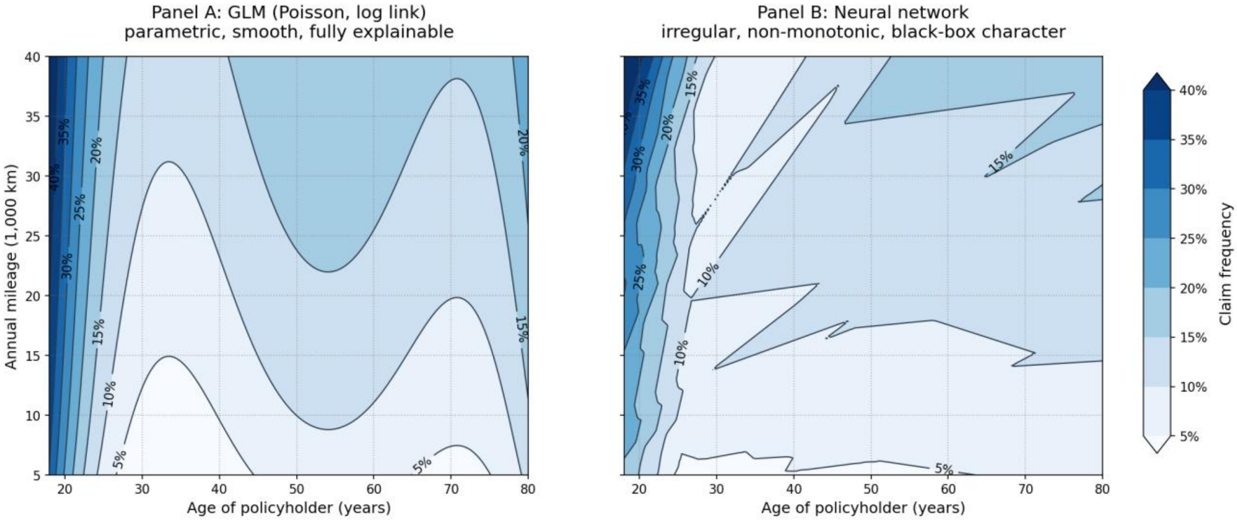


*Figure 1: Comparison of the solution spaces of a GLM (Panel A) and a neural network (Panel B) on an identical data basis. The GLM solution space is smooth, structurally traceable, and parametrically describable; the solution space of the neural network is more complex and less transparent, with structures that are in places locally irregular and non-monotonic.*

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## About the DAV

***Founded in 1993 and headquartered in Cologne, the German Association of Actuaries (Deutsche Aktuarvereinigung (DAV) e. V.) is the independent professional representation of the insurance, pensions, building society, and financial mathematicians working as actuaries in Germany. It creates the framework conditions for the professionally sound practice of its around 7,000 members and is in constant dialogue with all national and international institutions relevant to it, in order to contribute its professional expertise to legislative processes in the interests of actuaries and for the benefit of consumers and companies. As part of a demanding training programme alongside employment, it awards the title "Aktuar DAV" or "Aktuarin DAV" (Actuary DAV). In addition, it offers its members the opportunity to acquire further titles in order to demonstrate their qualifications in the fields of occupational pensions, risk management, and data science.***

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