Sound Practices for Responsible Adoption of Artificial Intelligence (AI): Consultation report

Response to Consultation

Association of German Banks

1. Do you agree with the benefits and risks of AI adoption by financial institutions described in this report? Are there any substantive benefits or risks not covered?

We broadly agree with the benefits and risks described in the report. The report correctly identifies AI as a tool that can support efficiency, fraud prevention, AML/CFT, cyber defence, internal controls, customer service, credit processes and operational resilience. These benefits are of significant value to the banking sector and should be supported by a regulatory approach that enables the responsible adoption of AI.

Regarding the described risks, the report should also give emphasis to the risk of regulatory uncertainty and fragmented interpretation. Where AI adoption is addressed through several overlapping regulatory and supervisory frameworks, institutions may face disproportionate implementation burdens or delay beneficial use cases. This is particularly relevant in the banking sector, where AI-specific requirements interact with existing financial-sector regulation, frameworks for operational resilience (e.g. DORA in EU), data protection law or consumer credit rules.

The report should also place more emphasis on the risk of non-adoption. If legal uncertainty or over-lapping requirements make responsible AI adoption too burdensome, banks may be less able to use AI for risk mitigation purposes such as fraud detection, cyber defence, AML/CFT, operational resilience or efficiency gains.

2. Are the sound practices sufficiently comprehensive and clear to enable financial institutions' responsible AI adoption?

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3. Do the sound practices strike an appropriate balance between managing risks relating to all forms of AI, and addressing some of the risks relating to emerging and new complex forms of AI, such as GenAI and agentic AI?

The report usefully differentiates between traditional AI and more complex forms of AI, such as GenAI and agentic AI. This differentiation should be further refined by clarifying the terms traditional AI and machine learning. It must be assured, that well established statistical methods such as standalone linear models or generalized linear models, such as logistic regression, are not mistakenly classified as AI Systems. Such methods should not be treated in the same way as opaque, adaptive, generative or autonomous AI systems. The relevant distinction should be functional: AI-specific safeguards should only apply where the overall system architecture creates AI-specific risks, for example through dynamic feature generation, automated retraining, limited explainability, generative outputs or autonomous execution.

4. **Are the sound practices sufficiently flexible to accommodate and address newer types of AI and responsible adoption over time?**

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5. **Do the case studies in this report sufficiently highlight how different types of financial institutions can benefit from responsible AI adoption? Are there additional case studies for inclusion in the report? If so, please provide such case studies, particularly for nonbanks.**

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6. **Do the case studies in this report provide actionable insights for financial institutions in their responsible AI adoption?**

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7. **Are the definitions in the glossary clear and aligned with industry sound practices, including recent developments in AI?**

   We suggest clarifying the glossary to avoid an overbroad classification of established statistical methods as Artificial Intelligence. As currently described in the report, the interaction between the definitions of Artificial Intelligence, machine learning and traditional AI leaves uncertainty as to which methods are intended to be captured and which methods should remain outside the scope of AI.

   In our view, standalone statistical methods such as linear models, generalised linear models and logistic regression, can be described as machine learning, but should not be classified as Artificial Intelligence where they operate on the basis of a predefined functional form, transparent coefficients, reproducible outputs and established model-risk governance.

   The report defines Artificial Intelligence as “a machine-based system 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”. It defines machine learning as “a method of designing a sequence of actions, known as algorithms, to solve a problem, which optimise automatically through experience and with limited or no human intervention”. Finally, traditional AI is defined as “a suite of computational techniques, such as longstanding machine learning methods, that pre-date recent advances, such as GenAI”.

   These definitions should be further clarified to avoid treating all longstanding machine-learning or statistical methods as AI. The decisive element in the AI definition is that the system infers how to generate an output from the input it receives. Logistic regression does not satisfy this element where it is used as a standalone statistical model. It does not independently infer or adapt the method by which outputs are generated. Instead, the functional form is specified in advance by humans; the relationship between inputs and outputs is determined through transparent and auditable parameters; and the model applies this predefined statistical specification to input data in a reproducible manner.

We therefore recommend refining the definition of “traditional AI” or adding an explanatory note to clarify that standalone statistical methods, including logistic regression, linear models and generalised linear models, should not be considered Artificial Intelligence.

Proposed explanatory note for definition of traditional AI: traditional AI does not include standalone statistical methods, such as linear models, generalised linear models or logistic regression, where these methods operate on the basis of a predefined functional form, transparent and auditable parameters, reproducible outputs.

This clarification is important for proportionality and technology neutrality. Established statistical models such as logistic regression are already subject to mature governance, validation, back-testing, monitoring and audit processes under existing model-risk management frameworks. Treating these methods as AI would risk overstating their risk profile and could divert supervisory and institutional resources away from genuinely AI-specific risks, such as opacity, autonomy, adaptivity, generative behaviour or insufficient human oversight.

8. Are there any comments you would like to make on this report? Please fill in.

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