Targeted consultation on artificial intelligence in the financial sector

Fields marked with * are mandatory.

Introduction

In financial services and beyond, there is a broad technology-driven trend towards greater use of AI. The Commission highlighted the need for a targeted consultation on the use of AI in financial services. The goal is to identify the main use cases and the benefits, barriers and risks related to the development of AI applications in the financial sector.

In general, the development and use of AI in the EU will be regulated by the AI Act, the world's first comprehensive AI law. The AI Act which was voted by the European Parliament on 13 March and expected to enter into force in July, aims to guarantee the safety and fundamental rights of people and businesses, while strengthening AI uptake, investment and innovation across the EU. To support further these objectives, an AI innovation package has been adopted by the Commission on 24 January 2024. It contains a series of measures to support European startups and SMEs in the development of trustworthy AI that respects EU values and rules. This follows the political agreement reached in December 2023 on the AI Act.

The AI Act is designed to complement the already existing financial services *acquis*, that, while not explicitly targeted at regulating AI, is an important framework to manage the related risks in specific applications and includes several relevant requirements for financial entities when providing financial services. It does so by pursuing objectives to ensure healthy financial markets, such as transparency, market integrity, investor protection and financial stability. For example, when providing investment services, including through reliance on AI such as trading algorithms, investment firms must comply with the MIFID/R framework and the market abuse rulebook.

The aim of this consultation is not to lead to policy work that would generate new duplicative requirements in relation to the use of AI by the financial sector, or to new requirements that have the potential to stifle AI innovation.

Objective of the consultation

The present targeted consultation will inform the Commission services on the concrete application and impact of AI in financial services, considering the developments in the different financial services use cases.

The views from stakeholders will support the Commission services in their assessment of market developments and risks related to AI and in the implementation of the AI Act and existing financial services legislation in the financial sector. The consultation is focused on the objectives of the financial sector *acquis* and the AI Act and is not intended to focus on other policy objectives such as competition policy. It is intended to improve the effective implementation of these legal frameworks.

This targeted consultation will include questions with multiple choice and open answers. The questionnaire contains three parts:

1. a first part with general questions on the development of AI
2. a second part with questions related to specific use cases in finance
3. and a third part on the AI Act related to the financial sector

For the purpose of this targeted consultation, the concept of AI corresponds to the definition of an AI system established in the AI Act, which covers "*any machine-based system 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*".

Target group

The targeted consultation will gather input from all financial services stakeholders including companies and consumer associations. Views are particularly welcome from financial firms that provide or deploy/use AI systems. This consultation is designed for respondents developing or planning to develop or use AI applications in financial services.

Responding to the consultation

Respondents are invited to complete the questionnaire by 13 September 2024. They are invited to elaborate by providing input and additional insights to their answers.

Outcome

Depending on the progress made, the Commission will publish a report on the findings and an analysis of the main trends and issues arising with the use of AI applications in financial services.

Please note that the information collected will not be shared with third parties and if used, it will be anonymised, in such a manner that it does not relate to any identified or identifiable financial institution.

Please note: In order to ensure a fair and transparent consultation process **only responses received through our online questionnaire will be taken into account** and included in the report summarising the responses. Should you have a problem completing this questionnaire or if you require particular assistance, please contact eu-digital-finance-platform@ec.europa.eu.

More information on

- this consultation
- the consultation document
- digital finance
- the digital finance platform

- [the protection of personal data regime for this consultation]

About you

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*Language of my contribution

- ( ) Bulgarian
- ( ) Croatian
- ( ) Czech
- ( ) Danish
- ( ) Dutch
- (•) English
- ( ) Estonian
- ( ) Finnish
- ( ) French
- ( ) German
- ( ) Greek
- ( ) Hungarian
- ( ) Irish
- ( ) Italian
- ( ) Latvian
- ( ) Lithuanian
- ( ) Maltese
- ( ) Polish
- ( ) Portuguese
- ( ) Romanian
- ( ) Slovak
- ( ) Slovenian
- ( ) Spanish
- ( ) Swedish

*I am giving my contribution as

- ( ) Academic/research institution
- (•) Business association
- ( ) Company/business

- Consumer organisation
- EU citizen
- Environmental organisation
- Non-EU citizen
- Non-governmental organisation (NGO)
- Public authority
- Trade union
- Other

* First name

Enrique

* Surname

Velazquez

* Email (this won't be published)

e.velazquez@accis.eu

* Organisation name

255 character(s) maximum

ACCIS

* Organisation size

- (selected) Micro (1 to 9 employees)
- Small (10 to 49 employees)
- Medium (50 to 249 employees)
- Large (250 or more)

Transparency register number

255 character(s) maximum

Check if your organisation is on the transparency register. It's a voluntary database for organisations seeking to influence EU decision-making.

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* Country of origin

Please add your country of origin, or that of your organisation.

- Afghanistan
- Åland Islands
- Albania
- Algeria
- American Samoa
- Andorra
- Angola
- Anguilla
- Antarctica
- Antigua and Barbuda
- Argentina
- Armenia
- Aruba
- Australia
- Austria
- Azerbaijan
- Bahamas
- Bahrain
- Bangladesh
- Barbados
- Belarus
- Belgium
- Belize
- Benin
- Bermuda
- Bhutan
- Djibouti
- Dominica
- Dominican Republic
- Ecuador
- Egypt
- El Salvador
- Equatorial Guinea
- Eritrea
- Estonia
- Eswatini
- Ethiopia
- Falkland Islands
- Faroe Islands
- Fiji
- Finland
- France
- French Guiana
- French Polynesia
- French Southern and Antarctic Lands
- Gabon
- Georgia
- Germany
- Ghana
- Gibraltar
- Greece
- Greenland
- Libya
- Liechtenstein
- Lithuania
- Luxembourg
- Macau
- Madagascar
- Malawi
- Malaysia
- Maldives
- Mali
- Malta
- Marshall Islands
- Martinique
- Mauritania
- Mauritius
- Mayotte
- Mexico
- Micronesia
- Moldova
- Monaco
- Mongolia
- Montenegro
- Montserrat
- Morocco
- Mozambique
- Myanmar/Burma
- Saint Martin
- Saint Pierre and Miquelon
- Saint Vincent and the Grenadines
- Samoa
- San Marino
- São Tomé and Príncipe
- Saudi Arabia
- Senegal
- Serbia
- Seychelles
- Sierra Leone
- Singapore
- Sint Maarten
- Slovakia
- Slovenia
- Solomon Islands
- Somalia
- South Africa
- South Georgia and the South Sandwich Islands
- South Korea
- South Sudan
- Spain
- Sri Lanka
- Sudan
- Suriname
- Svalbard and Jan Mayen

- Bolivia
- Bonaire Saint Eustatius and Saba
- Bosnia and Herzegovina
- Botswana
- Bouvet Island
- Brazil
- British Indian Ocean Territory
- British Virgin Islands
- Brunei
- Bulgaria
- Burkina Faso
- Burundi
- Cambodia
- Cameroon
- Canada
- Cape Verde
- Cayman Islands
- Central African Republic
- Chad
- Chile
- China
- Christmas Island
- Clipperton
- Grenada
- Guadeloupe
- Guam
- Guatemala
- Guernsey
- Guinea
- Guinea-Bissau
- Guyana
- Haiti
- Heard Island and McDonald Islands
- Honduras
- Hong Kong
- Hungary
- Iceland
- India
- Indonesia
- Iran
- Iraq
- Ireland
- Isle of Man
- Israel
- Italy
- Jamaica
- Namibia
- Nauru
- Nepal
- Netherlands
- New Caledonia
- New Zealand
- Nicaragua
- Niger
- Nigeria
- Niue
- Norfolk Island
- Northern Mariana Islands
- North Korea
- North Macedonia
- Norway
- Oman
- Pakistan
- Palau
- Palestine
- Panama
- Papua New Guinea
- Paraguay
- Peru
- Sweden
- Switzerland
- Syria
- Taiwan
- Tajikistan
- Tanzania
- Thailand
- The Gambia
- Timor-Leste
- Togo
- Tokelau
- Tonga
- Trinidad and Tobago
- Tunisia
- Turkey
- Turkmenistan
- Turks and Caicos Islands
- Tuvalu
- Uganda
- Ukraine
- United Arab Emirates
- United Kingdom
- United States

- Cocos (Keeling) Islands
- Colombia
- Comoros
- Congo
- Cook Islands
- Costa Rica
- Côte d’Ivoire
- Croatia
- Cuba
- Curaçao
- Cyprus
- Czechia
- Democratic Republic of the Congo
- Denmark
- Japan
- Jersey
- Jordan
- Kazakhstan
- Kenya
- Kiribati
- Kosovo
- Kuwait
- Kyrgyzstan
- Laos
- Latvia
- Lebanon
- Lesotho
- Liberia
- Philippines
- Pitcairn Islands
- Poland
- Portugal
- Puerto Rico
- Qatar
- Réunion
- Romania
- Russia
- Rwanda
- Saint Barthélemy
- Saint Helena Ascension and Tristan da Cunha
- Saint Kitts and Nevis
- Saint Lucia
- United States Minor Outlying Islands
- Uruguay
- US Virgin Islands
- Uzbekistan
- Vanuatu
- Vatican City
- Venezuela
- Vietnam
- Wallis and Futuna
- Western Sahara
- Yemen
- Zambia
- Zimbabwe

*Field of activity or sector (if applicable)

- [ ] Accounting
- [ ] Auditing
- [ ] Banking
- [ ] Credit rating agencies
- [ ] Insurance
- [ ] Pension provision
- [ ] Investment management (e.g. hedge funds, private equity funds, venture capital funds, money market funds, securities)
- [ ] Market infrastructure operation (e.g. CCPs, CSDs, Stock exchanges)
- [ ] Social entrepreneurship
- [x] Other
- [ ] Not applicable

* Please specify your activity field(s) or sector(s)

Credit referencing / credit scoring

The Commission will publish all contributions to this public consultation. You can choose whether you would prefer to have your details published or to remain anonymous when your contribution is published. **For the purpose of transparency, the type of respondent (for example, 'business association, 'consumer association', 'EU citizen') country of origin, organisation name and size, and its transparency register number, are always published. Your e-mail address will never be published.** Opt in to select the privacy option that best suits you. Privacy options default based on the type of respondent selected

* **Contribution publication privacy settings**

The Commission will publish the responses to this public consultation. You can choose whether you would like your details to be made public or to remain anonymous.

- ◯ **Anonymous**
  Only organisation details are published: The type of respondent that you responded to this consultation as, the name of the organisation on whose behalf you reply as well as its transparency number, its size, its country of origin and your contribution will be published as received. Your name will not be published. Please do not include any personal data in the contribution itself if you want to remain anonymous.
- ◉ **Public**
  Organisation details and respondent details are published: The type of respondent that you responded to this consultation as, the name of the organisation on whose behalf you reply as well as its transparency number, its size, its country of origin and your contribution will be published. Your name will also be published.

☑ I agree with the personal data protection provisions

Part 1: General questions on AI applications in financial services

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Question 1. Are you using or planning to use AI systems?

- ◯ Yes, we are already using AI systems
- ◯ Not yet, but we plan to use AI systems within the next 2 years
- ◯ No, we are not using it and we don't plan to use AI systems within the next 2 years

Don't know / no opinion / not applicable

Question 2. What are the positive things you encounter when using AI?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 3. What are the negative things you encounter when using AI?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 4. Will you be deploying AI for new or additional processes within your organisation?

- Yes
- No
- Don't know / no opinion / not applicable

Question 5. Are you developing or planning to develop in-house AI applications?

- Yes
- No
- Don’t know / no opinion / not applicable

Question 6. Which tools are you using to develop your AI applications?

Examples: machine learning, neural networks, natural language processing, large language models, etc.

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Benefits of using AI applications in financial services

Question 7. Please score the following benefits from most significant (10) to least significant (1):

	1 -	2	3	4	5	6	7	8	9	10 +	Don't know - No opinion - Not applicable
Fraud detection: AI algorithms can analyse large amounts of data to detect patterns and anomalies that may indicate fraudulent activity, helping to reduce financial losses for businesses and customers.											
Risk management: AI can analyse and predict market trends, assess credit risks, and identify potential investment opportunities, helping financial institutions make more informed decisions and manage risks more effectively.											
Automation of routine tasks: AI can automate repetitive tasks such as data entry, transaction processing, and document verification, freeing up time for employees to focus on more complex and strategic activities.											
Cost savings: by automating processes and improving efficiency, AI can help financial institutions reduce operational costs.											
Personalised financial advice: AI can analyse customer data to provide personalised financial advice and recommendations, helping customers make better financial decisions and improve their financial well-being.											

Compliance and regulatory support: AI can help financial institutions stay compliant with regulations by analysing and interpreting complex regulatory requirements and monitoring transactions for suspicious activities.											
Enhanced decision-making: AI can analyse large amounts of data and provide insights that can help financial institutions make better investment decisions, assess credit risks, and optimise their operations.											
Improved security: AI can enhance security measures by identifying potential security threats, detecting unusual patterns of behaviour, and providing real-time alerts to prevent security breaches.											
Streamlined processes: AI can streamline various financial processes, such as loan underwriting, account opening, and claims processing, leading to faster and more efficient services for customers.											
Improved customer service: AI can be used to provide personalised and efficient customer service, such as chatbots that can answer customer queries and provide assistance 24/7.											

Question 8. What are the main benefits/advantages you see in the development of your AI applications?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 9. Please score the following challenges from most significant (10) to least significant (1):

	1 -	2	3	4	5	6	7	8	9	10 +	I o ap
Lack of access to the required data, in general.											
Lack of access to the data in an appropriate digital format.											
Lack of access to appropriate data processing technology, e. g. cloud computing.											

Data privacy: it is crucial to ensure that sensitive financial information remains confidential.										
Lack of trust in relation to performance levels/ security aspects/ certified solutions/ reliability of the technology.										
Regulatory compliance with financial regulation: financial services are heavily regulated and not all types of AI applications are in line with requirements under these regulations.										
Innovation: the ability to leverage on combining AI with other technologies to enhance its potential and generate new services?										

Transparency and explainability: AI algorithms can be complex and opaque. It can be difficult for humans to understand how AI arrives at certain conclusions, which can create issues of trust and accountability.										
Bias and discrimination: AI models are trained using data, and if the data is biased, the AI model can also be biased, leading to unfair outcomes.										
Reputational risk from undesirable AI behavior or output.										
Liability risks: legal uncertainty on who bears the liability in case of damages generated by the malfunctioning of the AI applications.										

Skills gap: the development of AI requires specific tech skills, and there is a shortage of such skills.										
Dependability: as financial institutions rely more and more on AI; the dependability of these systems becomes paramount. Any malfunction or error (e.g. in risk management) can lead to significant financial losses.										
Job displacement: the use of AI can potentially automate certain roles in the financial sector leading to job displacement.										

Cybersecurity: AI systems could be targeted by cybercriminals, leading to potential data breaches or manipulation of AI systems.										
Integration challenges: integrating AI technologies with existing systems and processes can be complex and expensive.										
Additional cost: the deployment and use of AI requires up-front investment and ongoing resources (acquiring or developing applications, keeping them up to date, training/skills).										

Question 10. What are the main difficulties/obstacles you are facing in the development of your AI applications?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 11. Please rank the potential negative impact that widespread use of AI can have on the following risks, 8 being the highest risk:

	1	2	3	4	5	6	7	8
Operational risks								
Market risks								
Liquidity risks								
Financial stability risks								
Market integrity risks								
Investor protection risk								
Consumer protection risk								
Reputational risk								

Please explain your answer to question 11 and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 12. AI may affect the type and degree of dependencies in financial markets in certain circumstances, especially where a high number of financial entities rely on a relatively small number of third-party providers of AI systems.

Do you see a risk of market concentration and/or herding behavior in AI used for financial services?

- Yes
- No
- Don't know / no opinion / not applicable

AI and compliance burden

Question 13. Can AI help to reduce the reporting burden?

- Yes
- No
- Don't know / no opinion / not applicable

Question 14. Do you think AI can facilitate compliance with multiple regulatory standards across the EU and thus facilitate market integration or regulatory compliance?

For example, would you consider it feasible to use AI for converting accounting and financial statements developed under one standard (e. g. local GAAP) to another standard (e.g. IFRS)?

- Yes
- No
- Don't know / no opinion / not applicable

Please explain and elaborate on your answer to question 14 and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Data access

Question 15. In order to develop AI applications, do you need access to external datasets that you currently don’t have access to?

- Yes
- No
- Don’t know / no opinion / not applicable

Please explain your answer to question 15:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 16. Which datasets would you need to develop meaningful AI applications and for which purpose/use case?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 17. Do you face hurdles in getting access to the data you need to develop AI applications in financial services?

- Yes
- No
- Don't know / no opinion / not applicable

Question 18. Are you familiar with the EU Data Hub, a data sharing tool for supervisors and financial companies?

- Yes
- No
- Don't know / no opinion / not applicable

Question 19. Should public policy measures (e.g. legislative or non-legislative) encourage the exchange of data between market participants, which can be used to train AI systems for use cases in finance?

- Yes
- No
- Don't know / no opinion / not applicable

Business model

Question 20. Has AI changed your business model?

- Yes
- No
- Don't know / no opinion / not applicable

Question 21. Which parts of the value chain are being improved with AI?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 22. Are there functions that cannot/would not be improved by AI?

- Yes
- No
- Don’t know / no opinion / not applicable

General purpose AI

For the purpose of this targeted consultation, respondents should consider general purpose AI as defined in the AI Act (article 3(63)), i.e. meaning any “*AI model, including where such an AI model is trained with a large amount of data using self-supervision at scale, that displays significant generality and is capable of competently performing a wide range of distinct tasks regardless of the way the model is placed on the market and that can be integrated into a variety of downstream systems or applications, except AI models that are used for research, development or prototyping activities before they placed on the market*”.

Question 23. Do you use general purpose AI models, including generative AI, and their respective reference architectures?

- Yes
- Not yet, but we plan to use general purpose AI models within the next 2 years
- No
- Don’t know / no opinion / not applicable

Question 24. How do you plan to operationalise and adopt general purpose AI at scale?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 25. How does the increasing availability of general purpose AI models, including generative AI applications, impact the need to access new datasets?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 26. Compared to traditional AI systems such as supervised machine learning systems, what additional opportunities and risks are brought by general purpose AI models?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 27. In which areas of the financial services value chain do you think general purpose AI could have a greater potential in the short, medium and long term?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI Governance in relation to non-high risk use cases, and which are not subject to specific requirements under the AI Act

Question 28. Have you developed, or are you planning to develop an AI strategy or other relevant guidelines within your organisation for the use of AI systems?

- Yes
- No
- Don’t know / no opinion / not applicable

Question 29. Have you put in place or are you planning to put in place governance and risk management measures to ensure a responsible and trustworthy use of AI within your organisation?

- Yes
- No
- Don’t know / no opinion / not applicable

Forecasts

Question 30. What are the main evolutions to be expected in AI in finance?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 31. Which financial services do you expect to be the most impacted by AI?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question 32. Do you have any additional information to share?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Part 2: Questions related to specific use cases in financial services

Question 34. In which sector(s) are you using AI?

Please select as many answers as you like

- [x] Banking and payments
- [ ] Market infrastructure
- [ ] Securities markets
- [ ] Insurance and pensions
- [ ] Asset management
- [ ] Other

Questions per sector

Banking and payments

In banking, possible AI use cases range from credit risk assessment and credit scoring to advice, compliance, early warning (for example of unusual social media activity / massive withdrawal of deposits), fraud/AML and customer service.

Depending on the specific use cases, relevant legislation would include:

- the AI Act (for the identified high-risk use cases such as creditworthiness and credit-scoring of natural persons)
- the Consumer Credit Directive and the Mortgage Credit Directive (creditworthiness of natural persons and robo-advice)
- the Capital Requirements Regulation (CRR) (for example provisions on risk management in relation to credit risk assessment)
- the Payment Services Directives (PSD) (for example for fraud detection)
- and the Anti-Money Laundering Directive (AMLD) (for example for AML risk use cases)

Question BANKING 1. For which use case(s) are you using/considering using AI?

Examples: risk assessment, credit scoring, robo-advice, sustainable finance, personal finance management, regulatory compliance, fraud detection, AML, customer service, etc.

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Credit reference agencies are using/exploring the use of AI to help lenders evaluate the creditworthiness of individuals and businesses, as well as to establish credit scores. AI's ability to analyse vast and complex datasets allows it to identify patterns and correlations that traditional methods, such as logistic regression, might miss. This can lead to more accurate credit risk assessments.

However, it is important to note that traditional statistical techniques, particularly logistic regression, have long been the foundation of credit scoring. Even today, about 90% of credit scoring relies on these simpler statistical methods. Logistic regression, which is not in our view classified as AI under the AI Act (refer to our response to Question 39), remains a key tool in credit scoring due to its simplicity, transparency, interpretability, and regulatory acceptance. These characteristics make it easier for lenders and regulators to understand and trust the scoring process.

In addition to credit scoring, AI is being utilised by credit reference agencies to enhance KYC (Know Your Customer) checks, fraud detection, and customer identification processes (e.g., IBAN and name verification). These AI-driven services are crucial for complying with AML/CTF (Anti-Money Laundering/Counter-Terrorism Financing) legislation and aiding public authorities in combating fraud.

Question BANKING 2. What are the opportunities that AI brings to your use case?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Focusing on creditworthiness assessments and credit scoring, AI presents numerous opportunities, transforming how creditworthiness is assessed and enhancing the overall efficiency, fairness, and inclusivity of the process. Below are some key opportunities and their primary beneficiaries:

1. Improved predictive power:

AI can analyse vast datasets and identify complex patterns that traditional methods might miss, leading to more accurate predictions of credit risk. Machine learning models improve over time as they are exposed to more data, continually refining their predictive capabilities.

o Lenders: Gain more accurate assessments of credit risk, reducing defaults and improving loan portfolio quality. As shown by research from ACCIS member CRIF jointly with Intesa in the study: “Machine Learning for Credit Risk Management and IRB models|: lessons from successful case histories” [See: https://www.crif.digital/whitepapers/machine-learning-for-credit-risk-management-and-irb-models/], machine learning provides superior performances, particularly when used on highly granular data, whose richness may not be fully used by traditional techniques. As a result, loan decisions may become faster and more accurate, allowing institutions to develop new business, save on operating costs, drive down unexpected losses and raise risk-adjusted returns on capital.

o Consumers: Benefit from more comprehensive and accurate credit evaluations, increasing financial inclusion and protection against over-indebtedness. Research from ACCIS member Experian shows that machine learning-based credit scoring is 5.6% more accurate overall, with performance gains of up to 12.2% in young and risky segments.

o Market: Enables a more competitive and efficient credit market. More accurate creditworthiness assessments allow consumers to choose from a wider range of lenders, and lenders to offer more competitive terms, reducing bad debt and potentially lowering prices across the market.

2. Reduction of bias and promotion of fairness:

AI can help develop more precise and fairer credit scoring systems, fostering greater trust from consumers and regulators. AI can also identify and correct biases in credit scoring models, promoting fairer outcomes across different demographic groups. See further details here: For example, see https://www.researchgate.net/publication/335700394_Anti-discrimination_Law_AI_and_Gender_Bias_in_Non-mortgage_Fintech_Lending

o Consumers: Benefit from fairer credit assessments, reducing discrimination and ensuring more equitable access to credit.

o Regulators: Gain confidence that credit scoring systems comply with legal standards and ethical practices.

3. Enhanced financial inclusion:

Improved credit scoring systems can particularly benefit individuals with limited traditional credit histories, often including minority and low-income groups.

4. Optimisation of operations:

By increasing efficiency in risk management techniques, AI models can lower the costs of lending and offer opportunities to inspect and re-optimise lending decisions. For more details, see 31, 32 in this document: https://www.fsb.org/wp-content/uploads/P011117.pdf)

Question BANKING 3. What are the main challenges and risks that AI brings to your use case (e.g discrimination, opacity of the AI application developed, difficult to control/supervise it, etc.)?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI in credit scoring presents several challenges and risks:

1. Opacity and interpretability: AI models, particularly complex ones, can function as "black boxes," making it difficult to understand and explain how decisions are made. This lack of transparency can be problematic for consumers and regulators who require clear explanations of credit decisions. However, significant research has been undertaken to minimise these risks. Techniques now allow AI providers to explain decisions. Models are rigorously tested and recalibrated before deployment to ensure accuracy and fairness. Post-market monitoring ensures the model remains accurate and unbiased, reducing the presence of "black boxes" in credit referencing agencies.

2. Bias and fairness: AI systems can perpetuate or amplify existing biases if trained on biased data. However, this risk is not unique to AI; any system can propagate bias if based on poor data, leading to unfair credit scoring outcomes. Two clarifications as regards the credit reference sector:

Clarification 1: Some argue that AI increases bias risk due to larger training datasets and less transparent algorithms. However, in credit scoring, "big data" (i.e., vast, unstructured data from sources like social media) is not used. Instead, specific, supervised data related to financial behaviour is employed. Sophisticated AI techniques are explainable, and recent developments allow verification of how decisions are made and detection of bias. Thus, the claim that big data and complex algorithms heighten bias risk is not applicable to credit scoring.

Clarification 2: Some stakeholders argue that logistic regression should be treated as an AI system due to its risk of discrimination and therefore be accountable under the AI Act. This view is incorrect and contradicts the AI Act's intended approach. The AI Act first determines whether a system qualifies as AI, then assesses its risk level. Discrimination risk alone cannot classify a system as AI, as even human decisions carry bias. Logistic regression's risk of bias is well-known and has been addressed by financial regulators like the ECB and EBA through existing regulations (e.g., GDPR, CCD2, MCD, Capital Requirements Regulation, and EBA Guidelines). Ignoring this legal framework would imply that credit decisions have been biased for the past 50 years, which is misleading. In this regard, we invite the Commission to consult with the ECB and the EBA on how logistic regression models are appropriately supervised and are "accountable" and thus can be trusted.

3. Data quality, integrity, privacy, and security: AI relies on large amounts of high-quality data. If data is incomplete, inaccurate, or biased, it can lead to flawed outputs, even if these don't directly impact credit decisions. Ensuring the privacy and security of data is crucial, as breaches can have severe consequences. However, these challenges are not exclusive to AI.

Other general Challenges:

4. Regulatory risk: The definition of an AI system in the AI Act is unclear, creating uncertainty about whether basic machine learning techniques, such as logistic regression, are classified as AI. Credit agencies have used simple statistical methods like logistic regression in creditworthiness models for decades. These methods are transparent and explainable. The ECB's legal opinion (December 2021) argues that models using traditional statistical techniques should not be classified as high-risk AI. ACCIS strongly recommends that the Commission clarify that such models are excluded from the AI system definition.

5. Enforcement risk: The enforcement of the AI Act by regulatory authorities is also uncertain and could hinder AI adoption, leading to a less efficient credit market. Concerns include:

a) How will authorities explain and enforce requirements for high-risk systems?
b) How will authorities coordinate with data protection and financial regulators to ensure consistent and proportional regulation?

6. Compliance risk: AI models must comply with various regulations and industry standards, which can be challenging due to their complexity and the evolving nature of AI. Ongoing monitoring and validation are necessary to ensure compliance.

7. System integration: Integrating AI systems with existing processes and technologies can be complex and resource-intensive. Ensuring AI tools work seamlessly with legacy systems is crucial for maximising their effectiveness.

8. Over-reliance on AI: Relying too heavily on AI systems without sufficient human oversight can lead to erroneous decisions or overlooked contextual nuances.

Question BANKING 4. What is the main barrier to developing AI in your use case (e.g. lack of skills and resources, readiness of the technology, high regulatory costs for compliance with the relevant frameworks, etc.)?

Please explain and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

In a commissioned study conducted by Forrester Consulting on behalf of an ACCIS member (Experian) in 2021 [See: https://experianacademy.com/blog/2022/04/11/new-insight-report-explainability-ml-and-ai-in-credit-decisioning/], about 600 decision makers from the financial services and telecommunications sectors were asked which were the top barriers to AI/ML adoption. The three top barriers were: (i) Explainability of machine learning models (35% respondents mentioned this barrier); (ii) Model deployment into decisioning strategy management systems (35%) and lack of sufficiently wide range of traditional plus non-traditional data (31%).

Following the AI Act, these challenges are likely to intensify, particularly the need for transparent and explainable AI systems, which are mandatory for compliance. Moreover, legal uncertainty - such as the definition of AI systems- and the consequent costs will likely represent additional barriers to AI use in the sector.

Question BANKING 5. Does AI reduce or rather increase bias and discrimination in your use case?

- Yes
- No
- Don’t know / no opinion / not applicable

Please explain your answer to question BANKING 5 and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

As mentioned above, AI - like any other predictive method - can reduce or increase bias depending on the input data used.

On one hand, AI can enhance fairness by leveraging data-driven decision-making. By objectively analysing larger amounts of data, AI can reduce human biases that might influence credit decisions. Algorithms can be designed to exclude discriminatory factors (such as race) and focus solely on financial behaviours and creditworthiness. Additionally, advanced AI models can include fairness constraints and bias detection mechanisms, helping to identify and mitigate unfair treatment of specific groups. Continuous monitoring and auditing of AI systems can ensure that any emerging biases are detected and corrected promptly.

On the other hand, AI can also increase bias and discrimination if not properly managed. If the data used to train AI models contains historical biases or reflects existing societal inequalities, the AI – like any other type of model or technique – can perpetuate or even amplify these biases. For instance, if certain demographic groups have been historically underserved or unfairly treated by financial institutions, AI models can learn and repeat these patterns as other traditional models do. This issue is therefore not exclusive to AI models but pertains to any kind of predictive model, as it fundamentally relates to the quality of the data used. If the underlying data contains biases or reflects societal inequalities, any model, whether AI-based or traditional, can perpetuate these biases. Ensuring high-quality, unbiased data is crucial for all types of models to make fair and accurate decisions.

As explained in the reply to Question 3 above, it has been said that the complexity and opacity of many AI models could exacerbate the risk of bias – as identifying and addressing discriminatory practices within AI systems could be more challenging. However, as also mentioned above, in the financial service sector, there have appeared several techniques that allow the explanation of how an AI system produces an output. For example, this paper (https://link.springer.com/chapter/10.1007/978-3-031-44064-9_26) examines the cost of explainability in machine learning models for credit scoring. The analysis is conducted under the constraint of meeting the regulatory requirements of the European Central Bank (ECB) using a real-life dataset of over 50,000 credit exposures. The results reveal a difference of 15 to 20 basis points in annual return on investment between the best-performing black-box model and the best-performing inherently explainable model as cost of explainability.

In conclusion, as with any other technique, AI techniques can either reduce or increase bias and discrimination in credit scoring, depending on the quality of the data, the design and implementation of the algorithms, and the oversight and auditing processes in place. In other words:

• More data used responsibly (with quality data, well-designed algorithms and good governance) leads to better outcomes for consumers (e.g. financial inclusion, better loan terms and less risk of bias).

• More (poor) data used badly (with badly designed algorithms and poor data governance) leads to bad decisions and outcomes for consumers (e.g. discrimination and more expensive credit for vulnerable consumers).

Question BANKING 6. Has general purpose AI opened new possibilities or risks in your use case?

- ○ Yes
- ○ No

Don’t know / no opinion / not applicable

Please explain your answer to question BANKING 6 and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Question BANKING 7. On whom do you rely for the development of your AI solutions?

- External providers
- In-house applications
- Partial collaboration with external providers
- Don’t know / no opinion / not applicable

Please explain your answer to question BANKING 7 and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Part 3: AI Act

In December 2023 the European Parliament and the Council reached a provisional political agreement on the first comprehensive AI framework, put forward by the Commission on 21 April 2021. The regulation was adopted by the European Parliament on 13 March 2024 and will enter into force later this spring once it has been published in the Official Journal of the EU. This horizontal *acquis* is applicable across all economic sectors.

The AI Act defines an AI system as “a machine-based system designed to operate with varying levels of autonomy, 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". Recital 11 further sets out the reasons for this definition, notably setting out that it is based on key characteristics that distinguish it from simpler traditional software systems of programming approaches.

The AI Act will establish two high risk use cases for the financial sector:

1. AI systems intended to be used to evaluate the creditworthiness of natural persons or establish their credit score, with the exception of those AI systems used for the purpose of detecting financial fraud
2. AI systems intended to be used for risk assessment and pricing in relation to natural persons in the case of life and health insurance.

The aim of this section is to identify which are your specific needs in order for the Commission to be able to adequately assist you with appropriate guidance for the implementation of the upcoming AI framework in your specific market areas, especially in particular to the high-risk use cases identified.

Scope and AI definition

Question 33. Which of the following use cases that could fall into the categorisation of high-risk are potentially relevant to your activity?

- (x) AI systems intended to be used to evaluate the creditworthiness of natural persons or establish their credit score
- ( ) AI systems intended to be used for risk assessment and pricing in relation to natural persons in the case of life and health insurance
- ( ) Both
- ( ) None
- ( ) Don't know / no opinion / not applicable

Question 35. Please explain the overall business and/or risk management process in which the high-risk use case would be integrated and what function exactly the AI would carry out:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

As a preliminary observation, Annex III of the AI Act classifies AI systems used for evaluating creditworthiness or establishing credit scores as high-risk, with the exception of those for detecting financial fraud. Recital 58 explains that this classification aims to protect individuals' access to essential services like housing, electricity, and telecommunications. However, there is no evidence indicating that credit assessments decisively impact access to these services.

For instance, reports from the European Federation of National Organisations working with the Homeless (2017, 2021) identify factors like lack of affordable housing, unemployment, and legal obstacles as primary causes of housing exclusion, with no mention of credit scores. Similarly, the European Commission's work on the digital divide does not link credit assessments to exclusion from telecommunications services. Moreover, a report for the European Parliament attributes energy poverty to high energy prices, falling household incomes, and inefficient homes, without citing credit scores as a factor. We are happy to provide detailed information on these documents.

Given this, we believe that AI systems used for creditworthiness assessments or credit scores should be classified as high-risk only if they are deployed at a stage that directly and significantly influences the outcome of a credit decision (or "access to financial resources").

Business process overview:

The AI system developed for credit scoring would be integrated into the underwriting process. Underwriting involves processing credit applications and deciding whether to approve or decline them. The key steps are:

1. Data acquisition: Collecting data from the credit applicant.
2. Customer identification: Verifying the applicant's identity.
3. Fraud assessment: Assessing the risk of fraud in the application.
4. Creditworthiness assessment: Evaluating the applicant's creditworthiness (likelihood of repayment), which includes credit scoring as an input.
5. Estimation of collateral/guarantees: Determining possible collateral or guarantees to secure the credit amount, if applicable.
6. Pricing definition and approval: Setting the credit terms (interest rates) and making the final decision.

In the credit reference industry, we develop two main types of AI systems related to underwriting:

- High-risk AI systems for credit scoring (Step 4 above).

- AI systems supporting narrow procedural tasks in the process, which are not classified as high-risk for reasons discussed in Question 37.

Zooming in on Step 4: credit score model development

The development of a credit score model, used by lenders in creditworthiness assessments, involves the following steps:

a) Data collection: Gathering relevant financial data (e.g., credit commitments and repayment history) from past borrowers to create a representative sample.

b) Data Preparation: Pre-processing the collected data by handling missing values, encoding categorical variables, and scaling numerical features. This ensures the data is accurate, complete, and free from biases.

c) Modelling: the pre-processed data is split manually into training and testing datasets. The model - using an AI technique such as machine learning - is then trained on the training dataset. During the training, the function searches for the best-fitting line (or curve) that describes the relationship between the input features (e.g. number of credit commitments) and the probability of the outcome variable (= the likelihood of credit default). Finally, if the modelling does not result in satisfactory results, the human analyst goes back to the previous step of data preparation. As mentioned above, logistic regression can also be used to find these relationships, however the key difference is its complexity: while a human could replace a logistic regression function to identify those relationships, this could not be possible with ML.

d) Model evaluation: After training, the model's performance is put into practice using a testing dataset. This consists of stress testing and scenario analysis to evaluate the model's performance under different conditions. This aims to ensure the model's accuracy, fairness, and reliability. If the results are not satisfactory, the human analyst starts the process again.

e) Model deployment: Once satisfactorily trained and evaluated, the model is deployed for use in credit scoring. Lenders can then use it as an input for assessing an applicant's creditworthiness.

f) Model monitoring and maintenance: Ongoing monitoring ensures the model remains accurate and unbiased. This includes recalibration or eventual retirement of the model if necessary.

In conclusion, the AI systems developed by our industry are primarily used in the "modelling" and "evaluation" steps (c and d above) of the credit scoring development process.

Question 36. Are there any related functions AI would carry out which you would suggest distinguishing from the intended purpose of the high-risk AI systems in particular to the use cases identified in question 34?

- (•) Yes
- ( ) No
- ( ) Don't know / no opinion / not applicable

Please explain your answer to question 36 and give examples when possible:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI techniques which are planned or are being used by the credit reference sector for related functions to credit scoring or the broader underwriting process – which are not high risk - include:

- AI systems to prevent financial fraud
- AI systems to classify relevant data for credits scoring purposes

Regarding AI systems to prevent financial fraud, certain ACCIS members provide AI systems (based on machine learning) to prevent financial fraud in the context of a credit application. These systems are not high risk because they are explicitly excluded from the use case definition (see. Nr. 5 of the Annex III to the AI Act and recital 58 AI Act).

See below for an explanation of AI systems used to classify relevant data for credit scoring purposes. These should not be covered as high-risk because they are intended to perform a preparatory task for an assessment, but also because they carry out a narrow procedural task.

Question 37. Please explain why these functions would/should in your view not be covered by the high-risk use cases set out in the AI act either because they would not be covered by the definition of the use case or by relying on one of the conditions under article 6(3) of the AI Act and explaining your assessment accordingly that the AI system would not pose a significant risk of harm if:

a) the AI system is intended to perform a narrow procedural task:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI systems to categorise transactional data for credit scoring purposes.

Certain ACCIS members provide ML engines to categorise raw transactional data from a consumer´s bank account into predefined categories (income and expenses). Such engines classify data but do not evaluate a person's creditworthiness or provide a score. Categorised transactional data is only one input that can be used in the decision-making process (for creating KPIs or model development).

Reasons for not being high risk: these AI systems are intended to perform a preparatory task to a creditworthiness assessment listed in Annex III and are therefore excluded from the high-risk category pursuant to Art. 6(3) (d) AI Act. Categorising transactional data is to be understood as part of the broader scope of organising data (including indexing), which is encompassed by the preparatory tasks referenced in recital 53 AI Act (cf. recital 53 AI Act: “The condition covers, inter alia, smart solutions for file handling, which include various function from indexing […] or linking data to other data sources […].”). The mere categorisation/indexing of data also does not constitute an evaluation and for this reason does not qualify as profiling within the meaning of Art. (52) AI Act; Art. 4 (4) GDPR.

Categorising data is not only a preparatory task, but also a narrow procedural task within the meaning of Art. 6 (3) (a) AI Act. Narrow procedural tasks are tasks of such narrow and limited nature that they pose only limited risks which are not increased through the use of a high-risk AI system. In parallel with the examples set out in recital 53 AI Act, the categorisation of raw transactional data is to be understood as one such non-risk-increasing narrow procedural task, as it organises data in a manner similar to the transformation of unstructured data into structured data or the classification of documents into categories. Such tasks, as outlined in recital 53, are procedural in nature and do not inherently increase risk when performed by an AI system: “The first such condition should be that the AI system is intended to perform a narrow procedural task, such as an AI system that transforms unstructured data into structured data, an AI system that classifies incoming documents into categories or an AI system that is used to detect duplicates among a large number of applications”.

b) the AI system is intended to improve the result of a previously completed human activity:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

c) the AI system is intended to detect decision-making patterns or deviations from prior decision-making patterns and is not meant to replace or influence the previously completed human assessment, without proper human review:

5000 character(s) maximum
including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

d) the AI system is intended to perform a preparatory task to an assessment relevant for the purpose of the use cases listed in Annex III of the AI Act:

5000 character(s) maximum
including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI systems to categorise transactional data for credit scoring purposes.

Certain ACCIS members provide ML engines to categorise raw transactional data from a consumer´s bank account into predefined categories (income and expenses). Such engines classify data but do not evaluate a person's creditworthiness or provide a score. Categorised transactional data is only one input that can be used in the decision-making process (for creating KPIs or model development).

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Question 38. At this stage, do you have examples of specific AI applications /use cases you believe may fall under any of the conditions from article 6(3) listed above?

Please describe the use case(s) in cause and the conditions you believe they may fall under:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI systems to categorise transactional data for credit scoring purposes. For additional information, please refer to the question above.

Question 39. Based on the definition of the AI system, as explained above (and in article 3(1) and accompanying recitals), do you find it clear if your system would fall within the scope of the AI Act?

- ○ Yes
- ● No, it is not clear/ easy to understand if it falls within the scope of the AI Act
- ○ Don’t know / no opinion / not applicable

Please specify in relation to what aspects and/or which algorithmic /mathematical models you do not find it it clear/easy to understand if they fall within the scope of the AI Act:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

No, it is not clear from Article 3 and Recital 12 whether logistic regression, when used on a stand-alone basis, falls within the definition of an AI system. Our interpretation suggests it does not. To ensure legal certainty, we urge the Commission to clarify this in its forthcoming guidelines.

Reasons why logistic regression should not be classified as AI:

1. Legislative history of the AI Act: Three critical points are: (i) The final text of the AI Act refers exclusively to machine learning and knowledge-based approaches as AI categories. Logistic regression, initially listed in Annex I of the proposal, was explicitly removed, suggesting it should not be classified as AI. (ii) The 3rd Presidency compromise from the Council specified that logistic regression would only be included if used in

conjunction with machine learning, indicating that logistic regression alone does not meet the AI definition. (iii) The OECD explanatory memorandum, which influenced the EU's AI definition, only mentions machine learning and knowledge-based approaches as AI techniques. Logistic regression is not listed, reinforcing the idea that it is excluded from the AI definition.

2. Criteria for AI: Recital 12 outlines criteria for a system to be classified as AI, covering both the construction and operational phases. ACCIS believes logistic regression fails to meet a key criterion related to the building phase: the capacity to infer. Recital 12 states that an AI system must “transcend basic data processing, enabling learning, reasoning, or modelling.” Logistic regression, while able to infer, is primarily focused on basic data processing and lacks advanced learning or reasoning capabilities. Specifically: (i) Logistic regression cannot autonomously adapt or update its model based on new information or feedback. It lacks advanced learning techniques such as deep learning, which are necessary for complex pattern recognition. (ii) It does not possess an inherent reasoning mechanism that allows for logical deductions or conclusions based on rules or relationships. (iii) Logistic regression assumes a linear relationship between input variables and outcomes and cannot capture complex or hierarchical data structures required for sophisticated modelling tasks. (iv) The modelling performed by logistic regression is simple enough to be manually replicated. While the AI Act does not require AI systems to be opaque, classifying such a simple model as high-risk AI would be disproportionate. It should instead be classified as “basic data processing.”

3. Sectoral and supervisory view: European financial regulators believe logistic regression models, which have been used for decades, should not be regulated the same way as advanced techniques like machine learning. The European Central Bank's legal opinion (dated 29 December 2021, available at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A52021AB0040) argues that creditworthiness models using traditional techniques like logistic regression should not be classified as high-risk AI. Similarly, in the EBA’s report on machine learning for Internal Ratings-Based (IRB) models [dated August 2023, available at https://www.eba.europa.eu/sites/default/files/document_library/Publications/Reports/2023/1061483/Follow-up%20report%20on%20machine%20learning%20for%20IRB%20models.pdf], the authority focuses exclusively on the more intricate models (rather than traditional techniques such as “regression analysis and simple decision trees”) because such models are less comprehensible and less transparent, rather than traditional techniques such as “regression analysis and simple decision trees”. Logistic regression is adequately covered by existing legislation, and issues related to discrimination would indicate poor compliance, not a regulatory gap.

4. Public policy perspective: Including logistic regression in the AI Act would be unnecessary, disproportionate, and contrary to "better regulation" principles. It could negatively impact EU competitiveness and increase costs for consumers. For further explanation as to why logistic regression should not fall with the scope of the AI Act, see The AI Act Should Be Technology-Neutral (datainnovation.org) (https://www2.datainnovation.org/2023-ai-act-technology-neutral.pdf). Additionally, it should be noted that the new Strategy Agenda of the EU 27 Heads of States and Government aims to enhance competitiveness by reducing regulatory burdens. Including logistic regression under the AI Act contradicts this goal.

Given these considerations, ACCIS and other financial services trade associations urge the European Commission and AI Office to clarify the AI system definition in forthcoming guidelines, specifically regarding logistic regression. There is notable inconsistency in how co-legislators and DG Connect interpret the final text of the AI Act on this issue.

AI Act requirements

Question 40. Bearing in mind there will be harmonised standards for the requirements for high-risk AI (Mandates sent to CEN-CENELEC can be monitored here), would you consider helpful further guidance tailored to the financial services sector on specific AI Act requirements, in particular regarding the two high-risk AI use cases?

- (selected) Yes
- No
- Don't know / no opinion / not applicable

Please explain on which specific provisions or requirements and on what aspects concretely you would consider helpful further guidance tailored to the financial services sector:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Yes. Harmonised standards by European standards organisations play a pivotal role in ensuring compliance and promoting the use of AI based on the presumption of conformity, as outlined in Article 40. However, while we expect horizontal standards as well as horizontal guidance from competent authorities under the AI Act to consider both the specific supply chain and the existing solid legislative and regulatory framework, we strongly support the development of further vertical standards and guidance, specifically tailored to AI creditworthiness systems. Standards and guidance should be principle-based and provide sufficient leeway for providers and deployers of AI systems in relation to the two high-risk use cases.

In particular, we would recommend the specification of standards and guidance related to:

Article 9 - Risk management framework for financial services

Guidance is necessary, to ensure consistency between internal risk management frameworks according to (i) existing legislation in place for financial institutions (as deployers of AI systems for credit scoring and (ii) rules applicable to credit reference agencies, as AI system providers.

Article 10 – Data and Data Governance

a) Definition of Bias/Fairness

There are no universally accepted standards for defining bias and fairness in creditworthiness assessments, either within the EU or globally. Multiple definitions often conflict, making it challenging to satisfy one definition without failing another. Studies reveal that fairness toolkits can offer conflicting results on an algorithm's fairness, as meeting all fairness conditions simultaneously is mathematically impossible [See: https://link.springer.com/article/10.1007/s43681-021-00067-y].

Moreover, once a definition of bias/fairness is chosen, there is no established standard for what level is acceptable in consumer credit risk assessments. This uncertainty over definitions and acceptable performance levels creates significant regulatory risk for AI systems used in creditworthiness evaluations. As highlighted, "the multitude of indicators for labeling an AI system as '(un)fair' and the lack of field-specific criteria make consistent judgments challenging for auditors." [See: https://link.springer.com/article/10.1007

/s43681-023-00291-8].

That regulatory uncertainty and risk increase the cost of compliance and disincentivise the use of such AI systems. That is a particularly acute problem given the definition of AI system is very wide and the fact that lenders are obliged by the mortgage and consumer credit directives to carry out the evaluation where they must use an AI system for creditworthiness assessments (i.e. a high-risk AI system).

b) Data Processing for Bias Detection and Correction

Article 10.5 is both sensitive and novel. Guidance is needed to clarify how providers of high-risk AI systems should comply with this provision concerning the processing of special categories of personal data. This is particularly crucial given that creditors, as providers of high-risk AI systems, are prohibited from processing such data under the Consumer Credit Directive.

Article 13. “Sufficiently transparent”

Article 13 mandates high-risk AI systems to be designed and developed in such a way as to ensure that their operation is “sufficiently transparent”. We would welcome guidance on what can be considered “sufficiently transparent” in an AI system for creditworthiness assessments, including the degree of explainability that is required.

Article 17 – Quality management system – As with Article 9 of the AI Act above, guidance on quality management systems would be necessary to ensure consistency between internal management frameworks and the AI legislation.

Article 72 and 26.5. Post-market monitoring

Guidance is necessary to ensure consistency between current frameworks applicable to financial institutions as deployers of AI systems for credit scoring and credit reference agencies as AI system providers in relation to post-market monitoring related to high-risk AI systems (in particular, monitoring of risks under DORA and NIS2). This guidance should be developed through the cooperation of all authorities competent for supervising and enforcing the current frameworks.

Article 73 and 26.5. Reporting of serious incidents

Guidance is necessary to ensure consistency between current frameworks applicable to financial institutions as deployers of AI systems for credit scoring and credit reference agencies as AI system providers in relation to incident reporting (in particular, incident reporting under DORA and NIS2). This guidance should be developed through the cooperation of all authorities competent for supervising and enforcing the current frameworks.

Financial legislation requirements

Question 41. Future AI high-risk use cases would also need to comply with existing requirements from the financial legislation.

Would you consider helpful further guidance meant to clarify the supervisory expectations for these use cases?

- (selected) Yes
- No, the supervisory expectations are clear
- Don’t know / no opinion / not applicable

Please explain why you would consider helpful further guidance and indicate if it should be high-level and principles based or tailored to specific use cases:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

Yes. Due to the specific supply chain, providers of AI creditworthiness systems and credit scores, such as credit reference agencies, are not typically directly supervised by financial authorities competent for enforcing financial services law, unlike deployers who are regulated as financial institutions. Given the complex governance structure of the AI Act in relation to the financial sector under Article 74.6 and the potential for varying approaches among Member States regarding responsible national authorities, we recommend the development of further guidance by financial authorities in cooperation with other authorities competent for supervising and enforcing the AI Act vis-a- vis credit reference agencies, where relevant. This guidance should be principle-based and delivered through dedicated guidelines to ensure consistency across the EU financial market and to prevent divergences among Member States, as well as inconsistencies in the supervision of AI system providers who are not regulated by financial authorities.

Specifically, it would be beneficial to have clarity on whether the EBA guidelines require providers to exceed the requirements set by the AI Act. For example, the Guidelines on loan origination and monitoring state that credit institutions should “understand the quality of data and inputs to the model and detect and prevent bias in the credit decision-making process, ensuring that appropriate safeguards are in place to provide confidentiality, integrity, and availability of information and systems,” take “measures to ensure the traceability, auditability, robustness, and resilience of the inputs and outputs,” and implement “internal policies and procedures ensuring that the quality of the model output is regularly assessed, using measures appropriate to the model’s use, including back testing the performance of the model.”

Question 42. There are other use cases in relation to the use of AI by the financial services sector which are not considered of high-risk by the AI Act, but which need to comply with the existing requirements from the financial legislation.

Would you consider helpful further guidance meant to clarify the supervisory expectations for these use cases?

- Yes
- No, the supervisory expectations are clear
- Don’t know / no opinion / not applicable

Question 43. Are you aware of any provisions from the financial *acquis* that could impede the development of AI applications (e.g. provisions that prohibit the use of risk management models which are not fully explainable or the use of fully automated services for the interaction with consumers)?

- Yes (selected)
- No, I am not aware of any provision(s) of this kind
- Don’t know / no opinion / not applicable

Please please indicate the *acquis*/provision in cause:

5000 character(s) maximum

including spaces and line breaks, i.e. stricter than the MS Word characters counting method.

AI systems for assessing creditworthiness are more accurate when they use more accurate and comprehensive credit data. The biggest discrepancy today in the single market is that, in some Member States, creditors only share negative data with other creditors via credit databases. This means AI systems in those countries can only use data on missed credit payments to predict credit risk. In most Member States, creditors also share positive data, such as the value of loans, payments made on time, credit limits and other highly predictive data fields. AI systems that use positive and negative data are more accurate, better at preventing over-indebtedness and better at improving financial inclusion. Legislation, regulation or guidance that promotes positive data sharing between creditors via credit databases will increase the development and deployment of more accurate AI systems to evaluate creditworthiness.

Additional information

Should you wish to provide additional information (e.g. a position paper, report) or raise specific points not covered by the questionnaire, you can upload your additional document(s) below. **Please make sure you do not include any personal data in the file you upload if you want to remain anonymous**.

The maximum file size is 1 MB.
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Useful links

More on this consultation (https://finance.ec.europa.eu/regulation-and-supervision/consultations-0/targeted-consultation-artificial-intelligence-financial-sector_en)

Consultation document (https://finance.ec.europa.eu/document/download/054d25f5-0065-488a-96fb-2bb628c74e6f_en?filename=2024-ai-financial-sector-consultation-document_en.pdf)

More on digital finance (https://finance.ec.europa.eu/digital-finance_en)

More on the digital finance platform (https://digital-finance-platform.ec.europa.eu/)

Specific privacy statement (https://finance.ec.europa.eu/document/download/698ef635-9053-43c2-b3a3-709e18c1f88a_en?filename=2024-ai-financial-sector-specific-privacy-statement_en.pdf)

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