STUDY
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Artificial Intelligence and the fisheries sector

Fisheries

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RESEARCH FOR PECH COMMITTEE

Artificial Intelligence and the fisheries sector

Abstract

This study reviews current artificial intelligence (AI) systems legislation, the AI techniques definition proposed by the AI Act and main applications of AI methods in the fisheries sector with special focus on applications to enhance traceability of fishery products, fishing gear selectivity, good practices, and potential to help young people finding jobs. Finally, this study offers policy recommendations relevant to EU decision-making to achieve a better use of AI systems in the fisheries sector.

This document was requested by the European Parliament's Committee on Fisheries.

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LIST OF ABBREVIATIONS

AFMA	Australian Fisheries Management Authority
AI	Artificial Intelligence
AIA proposal	Proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act)
AIS	Automatic Identification System
ANN	Artificial Neural Network
BN	Bayesian Network
CAP	Common Agricultural Policy
CCTV	Closed-Circuit Television
CFP	Common Fisheries Policy
CJEU	Court of Justice of the European Union
CNN	Convolutional neural network
COM	Common Organisation of the Markets
DCF	Data Collection Framework
DL	Deep Learning
EGD	European Green Deal
EM	Electronic Monitoring
EMFAF	European Maritime, Fisheries and Aquaculture Fund
EU	European Union
EUMOFA	European Market Observatory for Fisheries and Aquaculture
FAO	Food and Agriculture Organisation of the United Nations
FCR	Fisheries Control Regulation

FPS	Frontal protection systems
FROODS	Fishing Route Optimization Decision Support System
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation
GES	Good Environmental Status
GVA	Gross Value Added
H2020	Horizon 2020 EU research and innovation funding programme
IATTC	Inter American Tropical Tuna Commission
ICCAT	International Commission for the Conservation of Atlantic Tunas
ICES	International Council for the Exploitation of the Sea
IMO	International Maritime Organization
IOTC	Indian Ocean Tuna Commission
IUU	Illegal, Unreported and Unregulated
LO	Landing obligation
MCRS	Minimum Conservation Reference Size
ML	Machine Learning
MPI	Ministry of Primary Industries of New Zealand
MSFD	Marine Strategy Framework Directive
MSY	Maximum Sustainable Yield
NMFS	National Marine and Fisheries Services
NOAA	North Oceanic and Atmospheric Administration
OJ	Official Journal
PECH Committee	European Parliament's Committee on Fisheries
PET	Protected Endangered and Threatened species

RFMO	Regional fisheries management organisation
SDG	Sustainable Development Goal
SME	Small and Medium Enterprise
STECF	Scientific Technical Economic Committee on Fisheries
SVM	Support Vector Machine
TAC	Total Allowable Catches
TEU	Treaty on European Union
TFEU	Treaty on the Functioning of the European Union
UN	United Nations
US	United States of America
VMS	Vessel Monitoring System
WCPFC	Western and Central Pacific Fisheries Commission

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EXECUTIVE SUMMARY

This study reviews the main applications of Artificial Intelligence (AI) systems in fisheries and identifies current challenges for fisheries that have the potential to be dealt with through AI.

Legal analysis of relevant EU fisheries legislation that enables the use of AI systems

The AI-related legal analysis in fisheries found that: 1) there is no explicit reference to AI systems in the most relevant EU fisheries legislation, but there are references to digitalisation that could include AI systems; 2) the most relevant fisheries legislation is drafted in a way that enable the use of AI systems; 3) the broad-ranging nature of the Artificial Intelligence Act (AIA) proposal makes its application to the fisheries sector straightforward; 4) there are some concerns that the General Data Protection Regulation would require adaptation to the new realities brought by AI technologies; and, 5) several third countries are considering AI methods for further automation of Electronic Monitoring systems.

Analysis of the current and potential use of AI techniques in the fisheries sector

The review of AI techniques in fisheries revealed that: 1) Machine Learning (ML) approaches have been used to automate biological sample processing; 2) ML has been applied after image analysis and on acoustic data to count and measure organisms; 3) research on catch classification by species and sizes using AI has increased; 4) ML is being applied to automatically classify or determine fishers' behaviour; 5) knowledge-based and expert systems have been applied to early warning systems and marine spatial planning; 6) traditional rule-based expert systems have been mainly applied in data-limited situations; 7) statistical approaches, Bayesian estimation, search and optimization methods are not traditionally considered AI, but can be integrated into AI systems; 8) some of the uses identified are applied to stock assessments and species distribution models; and, 9) fishing vessels could improve energy efficiency and reduce their CO_2 footprint by using AI systems.

Specific fisheries topics discussion on the use of AI systems

Firstly, seafood in all of the supply chain is analysed: 1) AI shows promising uses for traceability and seafood product integrity; 2) limited data generation and collection is the main barrier; 3) the processing industry is starting to use AI systems in automation processes; 4) AI proofs-of-concept have been developed in the field of logistics; and, 5) ML has been used to infer consumer behaviour and economic growth forecasting.

The second topic analysed is the use of AI for more selective fishing techniques: 1) there is a mismatch between fisheries selectivity improvement management goals and industry's tools to comply with regulations; 2) species selectivity can be further improved with AI; and, 3) AI systems aimed at automated species forecasting and detection, identification and sizing of catches could allow improving fishing decisions and enable quota tracking.

The third discussion topic assesses the use of AI as a driving force for young people to seek jobs in fisheries: 1) AI, similarly to digitalisation, is likely to create new skilled jobs while decreasing the need for low skilled ones in the fisheries sector; 2) the marine transport sector has developed AI systems focused on ship failure prediction and anomaly detection that could be applied in fishing vessels; and, 3) a more digitalised and AI-based fisheries sector might attract new young talent, but will be competing against other industries currently offering higher incentives.

Good practices in fisheries that could be useful for future good practices within the fisheries sector when developing or using AI are also analysed. Best practices guidelines for different fishery facets are

commonly used by management organisations to increase their sustainability and AI technology should follow this example.

Finally, there are general AI groups and networks at the European level, but they lack marine domain knowledge to develop fit-for-purpose AI systems for fisheries. There is at least one European working group focusing on AI for fisheries and several fisheries groups where AI has been discussed, but there is a shortage of sufficient resources.

Conclusions and recommendations for AI systems use in fisheries

The last chapter summarizes opportunities and obstacles to the application of AI in the fisheries sector based on the findings of previous chapters.

Main opportunities identified are: 1) increased transparency of fishing activity and reduced impact on the environment, thereby improving the public image of the sector; 2) early warning, forecasting and spatial planning systems can help in the planning activities considering trade-offs between them; 3) accelerated and increased data acquisition and coverage for stock assessments, sustainability indicators evaluation and other management data needs; 4) increased economic sustainability of the fishing industry, by reducing operational costs; and, 5) the modernisation of fisheries and its subsequent attractiveness to the younger population.

Main obstacles identified are: 1) industry trust and reluctance; 2) initial costs and lack of expertise; and, 3) legal and bureaucratic uncertainty.

Although some AI approaches are considered black boxes (e.g. Artificial Neural Networks), there are other suitable AI methods to understand the basis, processes and model forecasts and their uncertainty (e.g. Bayesian Networks).

Finally, the study ends with the following policy recommendations for the best use of AI in fisheries and its supply chain:

1. Amend Regulations that are or will be subject to revision in this field to include a reference to AI systems and AIA definition in paragraphs where digital transformation and new technologies are mentioned.
2. Amend the AIA proposal to include the fisheries sector. Its Recital 3 currently reads "[…] in healthcare, farming, education […]", it could be amended to "[…] in healthcare, farming and fishery, education […]".
3. Promote formation of interdisciplinary fisheries experts with AI related skills and multidisciplinary teams (e.g., AI, biological, economic, and legal disciplines).
4. Find ways to incentivise job opportunities and promotion of multidisciplinary and interdisciplinary experts not only in academia but also in the private fishery sector.
5. Attract young workers and empower women with AI skills in fisheries sector jobs through dissemination of information programs and by providing adequate incentives.
6. Promote private data collection and sharing, including appropriate data aggregation and anonymization safety protocols to facilitate industry trust.
7. Support the development of good AI practices and standards for statistical validation and ground truth verification to increase consumer and industry trust in AI performance, also supported by strong science fit-for-purpose applications aligned with sustainability goals.

8. Regulate the role of AI technological providers, ensuring some degree of experience in fisheries to prevent untrustworthy and not-fit-for-purpose AI systems (e.g., establishment of audited registration programs).
9. Create regulations limiting the access of certain kinds of AI systems to the fisheries sector to help avoid their application in illegal or unethical activities (e.g., through regional fisheries management organisations (RFMOs) or registers for vessel compliance with sustainability practices from trustworthy organisations).
10. Support the development of good AI practice guidelines in fisheries through collaboration with stakeholders and organisations (e.g., RFMOs, certification agencies, NGOs) using mechanisms and principles proven to be successful in other types of fisheries best practices guidelines.
11. Promote AI awareness, both benefits and constraints, among managers and industry to improve adoption processes at the whole supply chain.
12. Promote collaboration between universities, firms, AI developers and other stakeholders in fisheries though specific funding, specialized centres, and multidisciplinary networks.
13. Promote technological development integrated with AI systems to develop more selective fishing gears and fishing strategies by funding AI research and vessels digitalisation.

1. INTRODUCTION

KEY FINDINGS

- The Artificial Intelligence Act (AIA) proposal harmonizes the rules on the development and use of products and services making use of AI technologies in the EU single market, in the private and public sectors.
- The AIA proposal recognizes the potential of Artificial Intelligence (AI) to help meet some of the sustainability challenges of the EU, which are aligned with UN Sustainable Development Goals (SDGs).
- The AIA proposal sets out a risk-based approach to regulating AI implications, to create an ecosystem of trust in the use of AI by EU citizens, where fundamental rights and ethical principles are respected.
- Fishing is an important economic activity in the EU and worldwide, intrinsically dependent on the productivity of the marine environment, which is variable, and still insufficiently understood. Therefore, achieving sustainable fisheries is a very challenging task.
- There is a growing need in fisheries science and management for larger amounts of data and highly trained experts, in which digitalisation and AI should play a central role.
- Recent scientific review publications support the use of AI to address UN SDGs in fisheries.

Considering technological advances in AI and the challenges that it brings, in April 2021, the European Commission adopted a proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on AI (Artificial Intelligence Act)[1] and amending certain Union legislative acts (COM (2021) 206 final; the AIA proposal). The proposal sets out a risk-based approach to regulate AI implications, both in the public and private sectors, to create an ecosystem of trust in the use of AI by EU citizens, where fundamental rights and ethical principles are respected. Equally, the EU intends to lead in setting the highest standards worldwide, so other countries could follow this example.

The European Parliament has shown great interest on the development and use of AI in the EU. As a reflection of this, the European Parliament set up in June 2020 a Special Committee on Artificial Intelligence in a Digital Age (AIDA Committee) to analyse the impact of AI on the EU economy. Furthermore, the European Parliament has adopted several resolutions on AI, including related to ethical aspects (2020/2012(INL))[2], civil liability (2020/2014(INL))[3], intellectual property rights (2020/2015(INI))[4], and education (2020/2017/INI)[5]. The European Parliament has also called on the Commission to continue addressing the challenges faced by the public and private sectors with digital

1 Proposal for a Regulation of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain Union legislative acts, COM (2021) 206 final, 21.4.2021.

2 European Parliament resolution of 20 October 2020 with recommendations to the Commission on a framework of ethical aspects of artificial intelligence, robotics and related technologies (2020/2012(INL)), P9_TA (2020)0275.

3 European Parliament resolution of 20 October 2020 with recommendations to the Commission on a civil liability regime for artificial intelligence (2020/2014(INL)), P9_TA (2020)0276, OJ C 404, 6.10.2021, p. 107.

4 European Parliament resolution of 20 October 2020 on intellectual property rights for the development of artificial intelligence technologies (2020/2015(INI)), P9_TA (2020)0277, OJ C 404, 6.10.2021, p. 129.

5 European Parliament resolution of 19 May 2021 on artificial intelligence in education, culture and the audiovisual sector (2020/2017(INI)), P9_TA (2021)0238.

transformations, so that AI can enable and support these sectors. The publications of studies and briefing notes on AI also show the importance that the European Parliament places on this matter.

The Commission points out that the proposition on the AIA proposal is consistent with the EU Charter of Fundamental Rights and the existing Union legislation on data protection, consumer protection, non-discrimination, and gender equality. It is also complementary to the GDPR (Regulation (EU) 2016/679 of the European Parliament and of the Council on the protection of natural persons regarding the processing of personal data and on the free movement of such data)[6] and other ongoing legislative measures that address problems posed by the development and use of AI, including liability issues related to new technologies. The proposal is also closely linked to the Data Governance Act (COM(2020)767)[7], the Open Data Directive (Directive (EU) 2019/1024)[8] and other initiatives under the EU strategy for data (COM(2020)66 final)[9], concerning the mechanisms and services for the re-use, sharing and pooling of data that are essential for the development of data-driven AI models of high quality. Currently, the main objective of the AIA proposal is to ensure that the use of AI is safe and respects existing laws on fundamental rights and Union values and contributes towards achieving Sustainable Development Goals (SDGs) (Vinuesa et al., 2020; Palomares et al., 2021). AI may have a positive impact on 134 targets (79%) among all SDGs (Vinuesa et al., 2020). The advantages provided by AI may also have a positive impact on several SDGs within the Economy group on 42 targets (70%) from these SDGs (Vinuesa et al., 2020). In the Communication 'Fostering a European approach to Artificial Intelligence' (COM (2021) 205 final)[10], the Commission highlighted potential safety issues such as risks emerging from human-robot collaboration, autonomous machines, or privacy issues with image recognition. However, this communication also highlights important potential benefits, such as new employment opportunities outweighing potential job losses, and an increase of citizen engagement initiatives.

Fishing is an important economic activity in the EU and worldwide, intrinsically dependent on the productivity of the marine environment, which is variable, sensitive, and still insufficiently understood. Therefore, achieving sustainable fisheries is a very challenging task. It demands, on the one hand, some stability in fishing opportunities to ensure a viable fishery sector. On the other hand, sustainable fisheries require some flexibility to adapt to critical ecological alterations if functioning of the ecosystem producing these resources is to be maintained despite high uncertainty and limited knowledge about the mechanisms that regulate it. Moreover, many fish stocks are natural resources whose distribution is not restricted to national boundaries (Baudron et al., 2021). The setting of measures able to counteract threats and adapt to changes (e.g., stock declines, global warming), while guaranteeing a sustainable activity from an economic, social, and environmental perspective, arises as one of the principal challenges faced by fisheries policy makers. These policies require matching fishing opportunities with fishing capacity, incorporating the ecosystems approach, implementing regionalization, improving fisheries sustainability through governance, and incorporating fisheries activities in the broader maritime dimension, where fishing is one element among multiple activities.

6 Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46 (General Data Protection Regulation), OJ L 119, 4,5, 2016, p. 1.

7 Proposal for a Regulation of the European Parliament and of the Council on European data governance (Data Governance Act), COM (2020) 767 final, 25.11.2020.

8 Directive (EU) 2019/1024 of the European Parliament and of the Council of 20 June 2019 on open data and the re-use of public sector information (Open Data Directive), OJ L 172, 26.6.2019, p. 56.

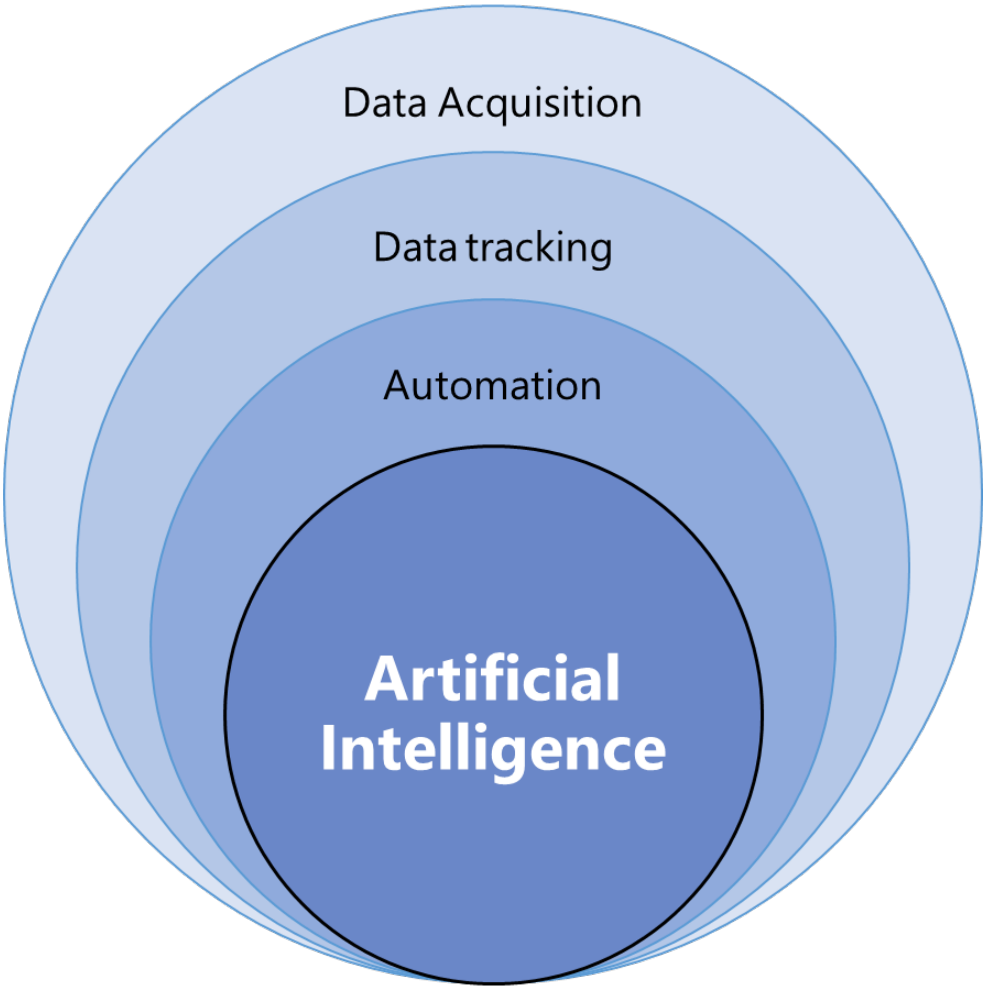
9 Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions 'A European strategy for data', COM (2020) 66 final, 19.2.2020.

10 Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions 'Fostering a European approach to Artificial Intelligence', COM (2021) 205 final, 21.4.2021.

The data produced by new technologies should contribute to a more sustainable exploitation, but there are still challenges regarding the use of this huge amount of diverse data to provide solutions to final users (Tanhua et al., 2019). The term big data was coined to capture the meaning of this emerging trend (Hu et al., 2014). In addition to its sheer volume, big data exhibits other unique characteristics when compared with traditional data. For instance, big data is commonly unstructured and requires real-time analysis. This development calls for new system architectures for data acquisition, transmission, storage, and large-scale data processing mechanisms (Boyes et al., 2014). AI is becoming a key factor in increasing the value of such data and has great potential for application in fisheries management and addressing industry challenges. AI systems, particularly the ones using Machine Learning (ML) approaches, have already proved their potential in many applications for fisheries, including: fisheries forecasting (Fernandes et al., 2010), automatic classification of samples (Irigoien et al., 2009), marine spatial planning for resolving conflicts of fisheries and new activities (Coccoli et al., 2018), emission reduction (Chan et al., 2021), fishing activities tracking (Taconet et al., 2019), fishing effort estimation (Behivoke et al., 2021), indicators (Uusitalo et al., 2016; Lehikoinen et al., 2019), species analysis for abundance indexes (Uranga et al., 2017), fishing gear selectivity (Joshy et al., 2018), traceability (Jothiswaran et al., 2020), species identification in EM (Lekunberri et al., 2022), and other topics as reviewed in this study. However, these are still preliminary and limited applications that do not yet fully exploit the vast potential for fisheries when combining ML and big data methodologies.

There is a growing need in fisheries science and management for larger amounts of data and highly trained experts, in which digitalisation and AI should play a central role. These data must be collected, stored, managed, and transmitted to different users. Therefore, the digitalisation in this sector is very important for achieving these purposes, and AI systems could play a critical role in the acquisition and use of the data. Digitalisation refers to enabling or improving processes by using digital technologies and data. However, a digital transformation process does not always necessarily imply the use of AI, despite its increasing presence in digitalized processes (Figure 1). This can create misunderstanding about some digitalisation approaches that can be useful for AI systems, but that strictly speaking are not AI approaches. Some examples are web scrapping and blockchain technologies. Web scrapping is the automation of data extraction from websites, whereas blockchain are blocks of data linked by cryptography. None of these examples are AI technologies but nonetheless can be used in combination with them. Ground truth/validation data and quality data for AI and fisheries science modelling is a challenge requiring findability, accessibility, interoperability, and reusability (FAIR) principles (Van Vranken et al., 2020). Four main challenges that can explain the lack of fisheries industry digitalisation are: upfront costs and insufficient access to capital, legal and bureaucratic barriers, failure to implement data collection standards, and lack of trust and buy-in from fisheries (Bradley et al., 2019).

Figure 1: Conceptual diagram showing the role of AI in relation with other digitalisation activities



Source: AZTI.

The European digital strategy aims to facilitate this, and the AIA proposal can be an opportunity to support this strategy. Legal and bureaucratic barriers need to be reduced to gain trust from the fisheries sector. Furthermore, a more digitalised industry with higher use of AI methods can lead to more environmental and economically sustainable industries, aligned with the European Green Deal (EGD)[11] strategy. To illustrate how AI methods and digital technologies are used or could potentially be developed in fisheries for a more digitalized and AI use industry, some examples are provided below:

- Catching sector: fishing vessels could improve energy efficiency that will significantly help to reduce fossil fuel consumption (fuel represents up to 50% of a fishing vessel's operational costs; Basurko et al., 2013), and reduce CO_2 emissions. Improved forecasting of fishing grounds by species could help fishers more effectively manage the use of their quotas and fishing effort. Furthermore, AI could contribute to a better collection, storage, and transmission of oceanographic and fisheries data from vessels to administrations and scientific institutes, providing more accurate and timely data.

[11] Communication from the Commission to the European Parliament, the European Council, the European Economic and Social Committee and the Committee of the Regions 'The European Green Deal', COM(2019) 640 final, 11.12.2019.

- Marketing of fishery products: the placing of fishery products in the internal market is one of the most important components of Common Organisation of the Markets (COM) which is one of the pillars of the CFP. Ensuring traceability of fishery products, avoiding mislabelling and fraud, ensuring public health and safety, fair prices for consumers and sellers, and guarantying fish sold is legally caught are areas where AI is utilized and could be further promoted.
- Administrations: public administrations could greatly benefit from the use of AI to digitalize their services, drastically reducing the amount of paperwork and simplifying everyday procedures. Administrators are critical actors since they need to collect, process, and transmit data to the European Commission. As previously stated, national policies can benefit from a more intensive use of AI, for the management of fleets and quotas, improving safety and security at sea, and the control of fishing activities that are very dependent on sophisticated technologies. Social and employment policies, education and vocational training could be further enhanced and promoted with the use of AI as well. The role of AI as a potential tool for fisheries management is recognised by the European Parliament, which in May 2021 issued the resolution (2019/2177(INI))[12] on securing the objectives of the Landing Obligation (LO) under Article 15 of the CFP. Amongst a set of management tools, the European Parliament recommended voluntary and incentive-based utilisation of AI for improving selectivity, control, and species identification.
- Marine spatial planning: AI is used for resolving conflicts of fisheries with current and new maritime activities (e.g. renewal energy and aquaculture; e.g. FutureMARES project[13]), and for the MSFD[14] indicators.
- Scientific Community: the scientific community is one of the most important users and developers of AI technologies in fisheries. The core of the scientific work is based on the data gathering processing and interpretation. AI is used for different purposes, for example fisheries forecasting, automatic classification of samples, analysing species for abundance indexes, estimating fishing gear selectivity to minimize the catch of unwanted species and to reduce the impact of fishing on marine ecosystems.

[12] European Parliament resolution of 18 May 2021 on securing the objectives of the landing obligation under Article 15 of the Common Fisheries Policy (2019/2177(INI)), P9_TA(2021)0227, OJ C 15, 12.1.2022, p. 9.

[13] www.futuremares.eu

[14] Directive 2008/56/EC of the European Parliament and of the Council of 17 June 2008 establishing a framework for community action in the field of marine environmental policy (Marine Strategy Framework Directive), OJ L 164, 25.6.2008, p. 19.

2. LEGAL ANALYSIS OF THE MOST RELEVANT EU AND THIRD COUNTRIES FISHERIES LEGISLATION THAT ENABLE THE USE OF AI SYSTEMS

KEY FINDINGS

- To date, there is no explicit reference to AI systems in the most relevant EU fisheries legislation, but there are references to digitalisation that could include AI systems' use.
- Many provisions of the most relevant fisheries legislation are drafted in a way that enable the use of AI systems.
- The broad-ranging nature of the AIA proposal makes its application to the fisheries sector straightforward.
- The fisheries legislation does not have any provisions that would hinder the implementation or undermine the coherence of the AIA proposal.
- The use of AI systems by operators in the fisheries sector is justified to improve the quality of their fishing activities and sustainability of fishing resources.
- There are some concerns that the General Data Protection Regulation would require a revision to adapt to the new realities brought by AI technologies.
- Several third countries (Australia, New Zealand, US) have started to implement electronic monitoring (EM) systems extensively and are considering AI methods for further automation.
- In these third countries, like in the EU, legislation has no explicit reference to AI systems.

The EU has ambitious goals for the use and protection of its natural resources, recently consolidated under the EGD. This strategy aims to transform the EU into a fair and prosperous society with a modern, resource-efficient, and competitive economy, where AI can play an important role in achieving these objectives. The objectives of the EGD, including the EU commitment, is to reduce emissions by 50-55% by 2030 and become net carbon-neutral by 2050. The EGD recognises that the EU should promote and invest in digital transformation for enabling decarbonisation changes. The EGD is aligned with other initiatives such as the SDGs, circular economy and Green Growth, the long-term strategy to support sustainable growth in the marine and maritime sectors (Blue Growth). Furthermore, the EGD aims to help the EU in its transition to a sustainable blue economy that promotes the use of smart digital solutions and autonomous systems in various sectors, including the fisheries sector (COM(2021) 240 final)[15]. Since the 1970s, and in particular since 1983 with the adoption of the Council Regulation (EEC) No 170/83 of 25 January 1983 establishing a community system for the conservation and management of fishery resources[16], the EU has been developing legislation regulating the activities of the fisheries sector. The 'fishery sector' is understood as 'the sector of the economy comprising all activities relating to the production, processing and marketing of fishery or aquaculture products'[17]. The most relevant EU fisheries legislation includes the provisions on: technical and conservation measures for marine

[15] Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions on a new approach for a sustainable blue economy in the EU: Transforming the EU's Blue Economy for a Sustainable Future, COM(2021) 240 final, Brussels, 17.5.2021.

[16] OJ L 24, 27.1.1983, p. 1.

[17] Article 5(d) of Regulation (EU) No 1379/2013 of the European Parliament and of the Council of 11 December 2013 on the common organisation of the markets in fishery and aquaculture products, amending Council Regulations (EC) No 1184/2006 and (EC) No 1224/2009 and repealing Council Regulation (EC) No 104/2000 (OJ L 354, 28.12.2013, p. 1).

biological resources; the management and control of EU fleets exploiting such resources; the processing and marketing of fishery and aquaculture products; the EU system to prevent, deter and eliminate IUU fishing; the international fisheries agreements concluded by the EU. In addition, the provisions concerning the European Maritime, Fisheries and Aquaculture Fund (EMFAF Regulation)[18] are of particular importance. Some of these provisions are currently under legislative review (e.g. Council Regulation (EC) No 1224/2009 on fisheries control system[19] – Fisheries Control Regulation) or will soon be under legislative review (e.g., Regulation (EU) No 1380/2013 of the European Parliament and of the Council of 11 December 2013 on the CFP[20] – Common Fisheries Policy (CFP) Framework Regulation; Directive 2008/56/EC of the European Parliament and of the Council of 17 June 2008 establishing a framework for community action in the field of marine environmental policy[21] – MSFD).

The current EU fisheries legislation does not make any explicit mention of AI. Only the most recent legislative declarations and especially the EMFAF Regulation refer, albeit indirectly, to AI. Thus, these legal acts contain references to the digital transition in the fisheries sector and in the EU blue economy. AI can be one of the elements that contributes to this transition (recital 51 and Article 8(5)(a) of the EMFAF Regulation). This normative context is easily understandable considering that the generalization of AI is recent, whereas legislative developments on fisheries began several decades ago (Churchill and Owen, 2010; Oanta, 2016; Penas, 2016). However, this absence of express references to AI in these normative texts has not prevented operators in several fisheries sectors from using AI systems in their activities as shown in this study. In the authors' view, the questions that arise are whether this fisheries legislation should expressly mention AI, and whether the AIA proposal should mention the primary sector of the economy, which includes fisheries, agriculture, forestry, and other, given their lower digitalisation and AI use in comparison to secondary and tertiary sectors (Södergård et al., 2021). At present, the AIA proposal only mentions Directive 2014/90/EU of the European Parliament and of the Council on marine equipment[22] (Directive 2014/90/EU) focused on security, but which affects fishing vessels too. Indeed, Article 78 of the AIA proposal contains an amendment to Article 8 of the Directive 2014/90/EU in the sense of adding a paragraph 4 to it, where AI systems are referred to according to which "For Artificial Intelligence systems which are safety components in the meaning of Regulation (EU) YYY/XX [on Artificial Intelligence] of the European Parliament and of the Council, when carrying out its activities pursuant to paragraph 1 and when adopting technical specifications and testing standards in accordance with paragraphs 2 and 3, the Commission shall take into account the requirements set out in Title III, Chapter 2 of that Regulation"[23].

This chapter is structured in four sections. The first section (2.1) identifies the most relevant fisheries legislation, highlighting provisions that make possible AI systems use with a summary table at the end. The second section (2.2) presents the provisions that need to be considered when using AI systems applicable to fishing activities, in particular the principles and values that inspire the process of

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[18] Regulation (EU) 2021/1139 of the European Parliament and of the Council of 7 July 2021 establishing the European Maritime, Fisheries and Aquaculture Fund and amending Regulation (EU) 2017/1004, OJ L 247, 13.07.2021, p. 1.

[19] Council Regulation (EC) No 1224/2009 of 20 November 2009 establishing a Community control system for ensuring compliance with the rules of the common fisheries policy, amending Regulations (EC) No 847/96, (EC) No 2371/2002, (EC) No 811/2004, (EC) No 768/2005, (EC) No 2115/2005, (EC) No 2166/2005, (EC) No 388/2006, (EC) No 509/2007, (EC) No 676/2007, (EC) No 1098/2007, (EC) No 1300/2008, (EC) No 1342/2008 and repealing Regulations (EEC) No 2847/93, (EC) No 1627/94 and (EC) No 1966/2006, OJ L 343, 22.12.2009, p. 1.

[20] OJ L 354, 28.12.2013, p. 22.

[21] OJ L 164, 25.06.2008, p. 19.

[22] Directive 2014/90/EU of the European Parliament and of the Council of 23 July 2014 on marine equipment and repealing Council Directive 96/98/EC, OJ L 257, 28.8.2014, p. 146.

[23] According to Article 78 of the AIA proposal, the Article 8(4) of Directive 2014/90/EU would set out as follows: 'For Artificial Intelligence systems which are safety components in the meaning of Regulation (EU) YYY/XX [on Artificial Intelligence] of the European Parliament and of the Council, when carrying out its activities pursuant to paragraph 1 and when adopting technical specifications and testing standards in accordance with paragraphs 2 and 3, the Commission shall take into account the requirements set out in Title III, Chapter 2 of that Regulation'.

European integration. The third section (2.3) includes a reference to the scarce jurisprudence of the Court of Justice of the European Union (CJEU) that has so far, directly, or indirectly, considered AI-related issues with projection on the fisheries sector. In the final section (2.4), the practice of third countries (e.g., Australia, New Zealand, and the US) regarding the use of AI systems in fisheries is examined.

2.1. Analysis of the most relevant EU fisheries legislation that enables the use of AI systems

As the relevant fisheries legislation in force is very extensive, this section focuses only on the EU secondary law that we consider to be the most significant and where we have identified provisions that already enable the use of AI elements by fishing operators. References to the legislative revisions in which several of them are involved at present will be mentioned as well.

2.1.1. The Common Fisheries Policy Framework Regulation

The CFP aims to ensure that fisheries and aquaculture activities are environmentally sustainable in the long term and are managed with the objectives of generating economic, social and employment benefits and contributing to the availability of foodstuffs (Article 2(1) of CFP Framework Regulation). CFP finds in the AI system an appropriate instrument for these purposes. Most AI systems in current use are data-driven despite expert knowledge also being required during the phases of design, data selection and interpretation. The CFP Framework Regulation refers to data collection and processing in several paragraphs since it considers that 'fisheries management based on the best available scientific advice requires harmonised, reliable, and accurate data sets' (recital 46). Additionally, it indicates that 'Member States should collect data on fleets and their fishing activities, in particular biological data on catches, including discards and survey information on fish stocks and on the potential environmental impact of fishing activities on the marine ecosystem. Member States should manage and make the collected data available to end-users and to other interested parties' (recital 46). Furthermore, this Regulation stresses that 'policy-oriented fisheries science should be reinforced by means of nationally adopted fisheries scientific data collection, research and innovation programmes' (recital 49). It also underlines the importance of exchanging relevant information to ensure sustainable exploitation of fisheries resources and management thereof consistent with the objectives of CFP (recital 51). Additionally, the CFP Framework Regulation includes the wish of promoting 'the use of modern and effective technologies […] in the framework of the Union control, inspection, and enforcement', stating that 'Member States and the Commission should have the possibility of conducting pilot projects on new control technologies and data management systems' (recital 60). It concludes by integrating private operators in data collection (recital 64). The reference in Recital 60 to new control technologies could be applicable to the use of AI system and the rest of recitals are applicable to the data needed to develop AI systems.

Within the articles of the CFP Framework Regulation, it is worth noting that Article 2, which sets out the objectives of the CFP, includes, in paragraph 4, that of contributing to the collection of scientific data. Article 3(k), when dealing with the principles of good governance, mentions 'transparency of data handling in accordance with existing legal requirements, with due respect for private life, the protection of personal data and confidentiality rules; availability of data to the appropriate scientific bodies, other bodies with scientific or management interest, and other defined end-users'. This principle of good governance also applies when the instrument used for this purpose is an AI system. There are other provisions in the CFP Framework Regulation that facilitate the use of AI. Thus, Part III of same, which contains the measures for the conservation and sustainable exploitation of marine biological resources, refers to conservation measures that may include measures to adapt fishing capacity of fishing vessels to available fishing opportunities (Article 7(1)l); to promote fishing methods that contribute to more selective fishing, avoidance and reduction, as far as possible, of unwanted catches, and with low impact on the marine ecosystem and fishery resources (Article 7(1)(d)); or, also to integrate into pilot projects on other types of fishing management techniques and fishing gear that increase selectivity or minimise the negative impact of fishing activities on the marine environment (Article 7(1)(h)). In this sense, AI systems can be developed as aids for technical measures aimed at the conservation of marine biological resources. In these provisions, reference is made to additional devices to improve selectivity or to minimise the negative impact on the ecosystem (e.g., vulnerable species bycatch reduction (Article 7(2)(b)). Thus, Article 14 focused on avoidance and minimisation of unwanted catches, and to facilitate the introduction of the LO, indicates that 'Member States may conduct pilot projects, based on the best available scientific advice and considering the opinions of the relevant Advisory Councils, with the aim of fully exploring all practicable methods for the avoidance, minimisation and elimination of unwanted catches in a fishery'. In the authors' view, these practicable methods include those based on AI.

Part IV of the CFP Framework Regulation deals with the management of fishing capacity (Articles 21-24), in the implementation of which the use of well-designed AI systems can be an important contributor to the fair and efficient establishment of systems required for transferable fishing concessions, adjustment and management of fishing capacity, entry and exit scheme for the EU Member States' fishing fleets or fishing fleet registers. Part V of the CFP Framework Regulation deals with the scientific basis for fisheries management, including data requirements for fisheries management purposes and the principles underlying the data collection, management, and use of such data (Article 25). This provision also applies when using the AI tools to automate data collection (e.g., classification of images of biological samples). Part VI of the CFP Framework Regulation deals with the external fisheries policy (Articles 28-33). These provisions set out, among other aspects, the sustainable fisheries partnership agreements (SFPAs) that enable the fishing activity of a significant part of the EU Member States' fleets (Oanta, 2017). This fishing fleet could employ AI instruments and its use would be included within the legal, environmental, economic and social governance framework defined in these agreements, with rules similar to those applicable to EU fishing vessels operating in the EU waters (Article 31). Part IX of the CFP Framework Regulation deals with the control and enforcement (Articles 36-39). Thus, Article 36(d) establishes the use of efficient control technologies to ensure the availability and quality of fisheries data. These technologies may include AI. Moreover, Article 38 refers to pilot projects on new control technologies and data management systems, stating that the 'Commission and the Member States may carry out pilot projects on new control technologies and systems for data management'. Potentially new systems that rely on AI could be an essential tool.

The CFP Framework Regulation will be revised soon. The European institutions, the Member States and, finally, the operators primarily concerned, are already making the first moves in this direction. The forthcoming debate seems an adequate time to examine the relevance of introducing explicit references to AI tools in the areas concerned.

2.1.2. The Fisheries Control Regulation

The success of CFP largely depends on the implementation of an effective control and compliance assurance system and here AI systems can facilitate such implementation. FCR dates back to 2009 and builds over CFP Framework Regulation and various initiatives adopted by the European institutions. There is no express mention of AI in the FCR, but it is possible to identify control, inspection and enforcement measures in which AI has the potential to ensure compliance with CFP rules. The FCR is concerned with the use of modern technologies to make the implementation of control, inspection, and enforcement measures more effective. This is evident when it underlines that 'modern technologies, such as the vessel monitoring system, the vessel detection system and the automatic identification system, should be exploited since they allow effective monitoring, systematic and automated cross-checks in a rapid manner'. These technologies would 'allow Member States to combine the use of the various control instruments to ensure the most efficient method of control' (recital 8). In the authors' view, such a broad statement implicitly covers AI new technologies.

The possibility of transmitting data from the Vessel Monitoring System (VMS), the Automatic Identification System (AIS), and the vessel detection system (recital 14,15), are also advantageous for the utilization of AI systems. It is the Council that will 'decide on the future use of tracking devices and traceability tools such as genetic analysis and other fisheries control technologies if these technologies lead to an improved compliance with rules of the CFP in a cost-effective way (recital 16). In the authors' view, this suggests that the Council will decide on the use of AI for these purposes and particularly for several aims of the recitals. The authors of this study consider that AI may be appropriate or could help to verify and control information on quantities of fish and fishery products declared by those involved in their landing and marketing (recital 18), and to improve controls on transhipments of fish on the high seas (recital 20). In addition, AI can be included in a coherent traceability system that applies to the whole supply chain of production and marketing of fish and fishery products (recital 28). Finally, AI falls within the concern highlighted by the FCR when it states that 'data collected and exchanged in the framework of this Regulation should be treated in accordance with applicable rules on confidentiality' (recital 48). However, in the authors' opinion, the confidentiality argument is overexploited by the sector to avoid sharing data. Additionally, this Regulation also notes that the EU rules 'on the protection of individuals regarding the processing of personal data and on the free movement of such data' should apply (recital 48).

Throughout the articles of the FCR, we also find provisions that can be related to AI systems. For instance, in Title II, General Principles, it is stated that 'Member States shall adopt appropriate measures, allocate necessary financial, human, and technical resources, and set up all administrative and technical structures necessary for ensuring control, inspection and enforcement of activities carried out within the scope of the CFP. They shall make available to their competent authorities and officials all adequate means to enable them to carry out their tasks' (Article 5(3)). In the authors' view, it would be understandable that these structures, techniques and means include AI systems. Moreover, the use of AI would facilitate the management of fishing licences (Article 6), fishing authorisations (Article 7), the marking of fishing gear (Article 8), the VMS (Article 9), the AIS (Article 10), the vessel detection system (Article 11), or the transmission of data for surveillance operations (Article 12). This would mean a considerable reduction of the administrative burden. Special mention should be made to Article 13, which refers to new technologies. Thus, under Article 13(2), 'The Council may decide based on Article 37 of the Treaty on the introduction of other new fisheries control technologies when these technologies lead to improved compliance with the rules of the CFP in a cost-effective way'. This provision, which was adopted in 2009, leaves the door open to the use of new technologies as they emerge, including AI.

Title IV of the FCR deals with the control of fisheries. In the authors' view, the provisions of this Title open up the possibility of applying AI tools in order to facilitate the control of the use of fishing opportunities (Chapter I), as regards: the transmission of fishing logbook data (Article 15), the prior notification (Article 17), the prior notification of landing in another Member State (Article 18), the authorisation to access to port (Article 19), the transhipment operations (Article 20), the completion and submission of the transhipment declaration (Article 21), the completion and submission of the landing declaration (Article 23), the control of fishing effort (Articles 26-32), and the recording and exchange of data by Member States (Articles 33-37). This technology could also be applied to the control of fleet management (Chapter II), or to the control of technical measures (Chapter IV), referring, for example, to fishing gear (Articles 47-49), particularly regarding catch composition (Article 49).

In Title V, the FCR contains the provisions concerning the control of the marketing of fish and fishery products. We consider that AI tools can facilitate the control of traceability of fishery and aquaculture products at all stages of the production, processing, and distribution chains, from catching or harvesting to the retail stage (Article 58(1)). Moreover, Article 66 and Article 67 of the Commission Implementing Regulation (EU) No 404/2011 of 8 April 2011 lays down detailed rules for the implementation of the FCR[24] setting out that traceability is to be ensured by adequate labelling for all fisheries and aquaculture products placed on the EU market. About the minimum labelling and information requirements for all fisheries and aquaculture products above, only the external identification number and name of the fishing vessel or the name of the aquaculture production unit could be seen as deserving special protection. The external identification number and name of the fishing vessel and the aquaculture production unit may allow the identification of private persons and companies when looking for information in fleet registers. This would fall under the definition of 'personal data' provided by Article 3 of Regulation 2018/1725 of the European Parliament and of the Council[25], whereby 'personal data means any information relating to an identified or identifiable natural person'. However, this is not the case in the EU register where the information of ownership is not publicly available.

Title XII of the FCR focuses on data and information. Thus, Article 109(1) states that 'Member States shall set up a computerised database for the purpose of validation of data recorded in accordance with' this normative act. Moreover, Article 109(2)(a) provides that 'Member States shall perform cross-checks, analyses and verifications of' data, using automated computerised algorithms and mechanisms, in particular concerning: VMS data; fishing activities data, in particular fishing logbooks, the landing and transhipment declarations and prior notifications; data from take-over declarations, transport documents and sales notes; data from fishing licences and fishing authorisations; data from inspection reports; data on engine power. Additionally, Article 109(2)(b) states that cross-checks, analyses and verifications shall be carried out, where appropriate, on the following data: vessel detection system data; data on sightings; data related to international fisheries agreements; data on entries into and exits from fishing zones, maritime areas where specific rules on access to waters and resources apply, regulatory areas of RFMOs and similar organisations and waters of third countries; and the AIS data.

The FCR is concerned with the confidentiality of personal and commercial data. In this regard, Article 112 and Article 113 of this normative act clearly state that the FCR in no way affects the level of protection of individuals with regard to the processing of personal data under Union law and domestic law of the Member States, and in particular does not alter the obligations of Member States relating to their registration and processing of personal data under GDPR, or the obligations of the Union and bodies relating to their processing of personal data under Regulation (EU) 2018/1725 when fulfilling their responsibilities. When Member States collect data and the Commission receives it, they have to ensure that these data are treated in accordance with applicable rules on professional and commercial secrecy of data. This implies that the data thus exchanged shall not be transmitted to persons other than those for which the data is intended. The data shall not be used for any purpose other than that provided in the FCR. When data is transmitted to third countries and RFMOs there should be a legal

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24 Commission Implementing Regulation (EU) No 404/2011 of 8 April 2011 laying down detailed rules for the implementation of Council Regulation (EC) No 1224/2009 establishing a community control system for ensuring compliance with the rules of the Common Fisheries Policy, OJ L 112, 30.4.2011, p. 1.

25 Regulation (EU) 2018/1725 of the European Parliament and of the Council of 23 October 2018 on the protection of natural persons with regard to the processing of personal data by the Union institutions, bodies, offices and agencies and on the free movement of such data, and repealing Regulation (EC) No 45/2001 and Decision No 1247/2002/EC (OJ L 295, 21.11.2018, p. 39).

basis for authorizing it, meaning that there must be an international agreement between the EU and the third country and RFMOs concerned whereby the European Commission is obliged to send that data. In any event, the level of protection on the personal data is decided by Member States in their national legislation.

Lastly, Article 115 and Article 116 of FCR establish the obligation for Member States to make an official website with publicly accessible information collected in the framework of the FCR, and a restricted or secured part. These provisions are also in line with the protection of personal data and confidentiality rules, and the use of these data by algorithms will have to be aligned with the rules governing data use, mainly the Data Governance Act and the Open Data Directive.

In the authors' view, the FCR would allow the possibility for AI tools to be applied for work on these data. We consider that AI tools would probably facilitate access to these data (Article 110) and the exchange of such data, and their functioning would still be subject to the confidentiality of data and the protection of personal data provisions (Articles 112-116). Currently, the FCR is under revision and in April 2018, the European Commission published the Proposal for a Regulation of the European Parliament and of the Council amending Council Regulation (EC) No 1224/2009, and amending Council Regulations (EC) No 768/2005, (EC) No 1967/2006, (EC) No 1005/2008, and Regulation (EU) No 2016/1139 of the European Parliament and of the Council as regards to fisheries control[26] (Commission proposal for the revision of the FCR). This soft law text revision represents an ideal time to question the convenience of including a reference to AI elements in the new FCR. This incorporation would make it possible, as indicated in the proposed Regulation, 'to effectively address current and future needs in terms of fisheries data and fleet control, to march the constant evolution of fishing practices and techniques, and to take advantage of modern and more cost-effective control technologies and data exchange systems'[27]. During the debate on the revision of the FCR, and in relation to the lack of control of the LO and the need to fully document fishing and by-catches of sensitive species, the desirability of progressing from traditional control methods to new digital systems has been highlighted. This would be in line with the Commission's proposal 'On a new approach to the EU's sustainable blue economy: Transforming the EU blue economy for a sustainable future'[28] when it considers that 'digitisation and advanced tools for fisheries (such as remote EM systems, catch reporting using mobile applications, ecosystem modelling and AI tools) can optimise fishing operations and at the same time enable data collection and analysis, improve control and monitoring, reduce administrative burden and ultimately support the sustainable management of marine biological resources without requiring physical presence'[29]. In addition, we consider that AI elements could be introduced into the legislative debates of the Commission proposal for the revision of the FCR. Indeed, AI elements could be mentioned in relation to: the fisheries control (a new recital between the current recital 15 and recital 16); the traceability information (a new recital between the current recital 36 and recital 37); data recording in digital form and availability of technological tools (recital 44); the use of collected data (recital 55); the data exchanges (recital 56); and processing of personal data (recital 58).

So far the European Parliament has already introduced certain amendments in its Report on the proposal for a regulation of the European Parliament and of the Council as regards fisheries control, which has been adopted on 10 February 2021[30]. In this regard, we could mention the amendments that emphasise the need for 'a straightforward, simple, transparent, and effective control system that

[26] COM (2018) 368 final.

[27] Ibídem, p. 1.

[28] COM(2021) 240 final, cit.

[29] Ibídem, p. 9.

[30] A9-0016/2021, 10.2.2021.

ensures effective, uniform, and up-to-date compliance in the Member States' (amendment 2) that takes 'into account the latest scientific findings with respect to the environmental sustainability of fishing and aquaculture activities' (amendment 3).

Finally, Amendment 123 [Proposal for a Regulation. Article–1 - paragraph–1 - point 23. Regulation (EC) No 1224/2009. Article 2–a - paragraph 3 b (new)] provides that 'in addition to EM systems used to check compliance with the LO, Member States may also support the use of systems, which make for closer monitoring of the selectivity of fishing operations directly on gear'. In the authors' view, these systems could be assisted by AI. This is reflected in the justification included in this Report. Thus, the European Parliament affirms that 'many innovations are being developed, such as 'real-time digital recognition software or other AI-based tools, which will allow a closer monitoring of the selectivity of fishing operations directly on gear. Since the purpose of the LO is to encourage greater selectivity, these tools must be used to make fishing operations more selective in nature, rather than simply promoting ex post monitoring of fishing operations by means of CCTV'. Furthermore, the rapporteur named by the European Parliament in relation to this report mentions explicitly that 'following the unanimous opinion of the experts consulted, the only way to carry out effective monitoring of the LO is to equip a minimum percentage of fishing vessels, identified under specific control and inspection programmes as representing a high risk of non-compliance with the LO and catching species subject to the LO, with continuously recording Closed-Circuit Television (CCTV) systems and/or other alternative discard monitoring systems incorporating data storage devices'.

The authors of this study consider that these ideas have been already put forward in the European Parliament's resolution adopted on 25 October 2016, which called on the Commission to review the FCR. This resolution envisaged a series of proposals, including 'the use of new monitoring and real-time information transmission and communication technologies' (paragraph 21).

2.1.3. Regulation on the sustainable management of external fishing fleets

The EU's exclusive competence for the conservation of fisheries resources is not limited to maritime waters under the sovereignty or jurisdiction of its Member States, but also extends beyond that to fishing activities of fishers and fishing vessels of Member States in the waters of third countries or on the high seas (Guggisberg, 2019; Sobrino Heredia and Oanta, 2015). It is in the development of this competence that the EU has adopted Regulation (EU) 2017/2403 of the European Parliament and of the Council on the sustainable management of external fishing fleets[31] (Regulation on the sustainable management of external fishing fleets). The main objective of this normative act is that 'any Union vessel fishing outside Union waters should be authorised by its flag Member State and monitored accordingly, irrespective of where it operates and the framework under which it does so [...]. The information gathered by the Member States and provided to the Commission should allow the Commission to intervene in the monitoring of the fishing operations of all Union fishing vessels in any given area outside Union waters' (recital 14).

AI tools could contribute to a better management of the requirement in the Regulation on the sustainable management of external fishing fleets according to which 'Member States should collect all requested data about their fleets and their fishing operations, manage those data and make them available to the Commission' and that they also should 'cooperate with each other, the Commission and third countries where relevant to coordinate those data collection activities' (recital 27). In the authors' view, the information collected and analysed by AI in real-time would enable the Commission to intervene at any time and in any place in the control of fishing operations of all Union fishing vessels

[31] Regulation (EU) 2017/2403 of the European Parliament and of the Council of 12 December 2017 on the sustainable management of external fishing fleets, and repealing Council Regulation (EC) No 1006/2008, OJ L 347, 28.12.2017, p. 81.

outside EU waters. In addition, and in relation to fishing authorisations, the Regulation on the sustainable management of external fishing fleets indicates that the Commission will set up an electronic database on fishing authorisations comprising both a publicly accessible part and a secure part. It clarifies that, as this database includes personal data, the processing of such data should comply with the provisions of EU law and applicable national law (recital 28). In relation to these operations, the Regulation on the sustainable management of external fishing fleets expressly states that 'a common system of data exchange and data storage should be used by the Member States and the Commission to provide necessary information and updates while minimising administrative burden'(recital 33). Precisely, one of the *raisons d'être* of the AI systems is to reduce this kind of administrative burden. It is also interesting to note that the Regulation on the sustainable management of external fishing fleets empowers the Commission to develop these issues by means of a delegated act to take account of technological progress (recital 36 and Article 44). Moreover, the provisions of this Regulation develop these issues and, in particular, Title IV focuses on the issue of data and information (Articles 39-43), potentially addressing aspects where AI technology can be developed, such as the management, maintenance and access to the database centralised in the Commission.

2.1.4. Regulation of the EU system to fight against IUU fishing

IUU fishing is one of the greatest threats to the sustainable exploitation of living aquatic resources and undermines the foundations of the CFP and international efforts to achieve better governance of the seas and oceans and is a major threat to marine biodiversity. Therefore, addressing IUU fishing impacts must be prioritised in a decisive and effective manner (Oanta, 2015; Rosello, 2017).

The EU adopted the Council Regulation (EC) No 1005/2008 establishing a Community system to prevent, deter and eliminate illegal, unreported and unregulated fishing[32] (IUU Regulation), which entered into force in January 2010. The scope of the Regulation on IUU Regulation is very broad as it covers fishing activities in the high seas and in maritime waters under the jurisdiction or sovereignty of coastal countries, including those under the jurisdiction or sovereignty of the EU Member States (recital 7). It aims at extending fisheries control measures to fishery products caught by third country fishing vessels and imported into the EU, allowing a proper control of the supply chain of fishery products imported into the Union (recital 9). To this end, the measures for the information, certification, control, inspection, and verification of fishery products imported into the Union are strengthened, supported by the EU alert system to report any doubts regarding the measures adopted by the flag states (recital 21), and establishing a list of IUU vessels drawn up by the Commission (recitals 26-29).

Several provisions of the Regulation on the EU system to fight against IUU fishing refer to the collection and handling of data, the use of electronic means (Article 8 and Article 14) or electronic traceability systems that ensure the same level of control by the authorities (Article 12). We consider that these are procedures that could be strengthened through the use of AI tools. However, the Regulation on the EU system to fight against IUU fishing does not explicitly provide for them. It has to be acknowledged that this Regulation predates the adoption of the CFP Framework Regulation and the FCR. It is also prior to the conclusion of the Food and Agriculture Organisation of the United Nations' (FAO) agreement on Port State Measures adopted in the fight against IUU fishing. In this regard, this study authors believe that the absence of an explicit mention of AI systems would not preclude their use in the measures adopted by the EU to combat IUU fishing. This would lead us to recommend that when this Regulation is revised, these AI instruments should be specifically considered. Furthermore, the legislative debates

[32] Council Regulation (EC) No 1005/2008 of 29 September 2008 establishing a Community system to prevent, deter and eliminate illegal, unreported and unregulated fishing, amending Regulations (EEC) No 2847/93, (EC) No 1936/2001 and (EC) No 601/2004 and repealing Regulations (EC) No 1093/94 and (EC) No 1447/1999, OJ L 286, 29.10.2008, p. 1.

related to the AIA proposal should make a reference to the provisions of the IUU Regulation under review, so as to include the mention of AI systems.

2.1.5. Regulation on the conservation of fisheries resources and the protection of marine ecosystems through technical measures

Setting out the technical measures to support the implementation of the CFP is Regulation (EU) 2019/1241 of the European Parliament and of the Council on technical measures[33] (Regulation on technical measures). It aims to prevent the capture of juveniles, non-commercial species, marine reproductive species and other marine animals by selective fishing gear means and the avoidance of unwanted catches. It establishes technical measures for the capture and landing of marine biological resources, the use of fishing gear and the interaction of fishing activities with marine ecosystems.

The technical measures aim to contribute to the achievement of the objectives of the CFP to fish at levels commensurate with maximum sustainable yield (MSY), to reduce unwanted catches and eliminate discards and to contribute to the achievement of good environmental status (GES). From this perspective, new technology tools such as AI systems can contribute towards these objectives and help avoid, minimise, and eliminate unwanted catches (recital 22), improve the application of innovative fishing gears (recital 30), and contribute to pilot projects on full documentation of catches and discards (recital 33). The AI tools may be an instrument to be used to achieve some of the objectives set out in Article 3 of the Regulation on technical measures. Furthermore, Article 6 of the Regulation on technical measures contains numerous definitions of fishing gears and various mechanisms associated with it. Indeed, Article 6(42) of this normative act sets out that 'gear monitoring sensors' have to be understood as 'remote electronic sensors that are placed on fishing gear to monitor key performance parameters such as the distance between trawl doors or volume of the catch'. These monitoring tools could be further improved with the integration of AI systems.

In summary, AI can be used to improve monitoring and control tools for fishing activities and targeting mechanisms, applicable both to fishing gear and conditions for its use (Article 8 and Article 9), the protection of sensitive species and habitats (Articles 10-12), to protect minimum conservation reference sizes (Article 13), and to enhance measures that reduce discards (Article 14). AI tools could also be included in pilot projects that develop comprehensive catch and discard documentation systems based on measurable objectives and targets for results-based fisheries management (Article 23). They could also be tools used in automatic size or sex grading equipment for certain fish species (Article 33)[34].

2.1.6. Regulation on the common organisation of the markets in seafood products

Regulation (EU) No 1379/2013 of the European Parliament and of the Council on the common organisation of the markets in fishery and aquaculture products[35] (Regulation on the common organisation of the markets in fishery and aquaculture products) provides for the legal framework for

[33] Regulation (EU) 2019/1241 of the European Parliament and of the Council of 20 June 2019 on the conservation of fisheries resources and the protection of marine ecosystems through technical measures, amending Council Regulations (EC) No 1967/2006, (EC) No 1224/2009 and Regulations (EU) No 1380/2013, (EU) No 2016/1139, (EU) 2018/973, (EU) 2019/472 and (EU) 2019/1022 of the European Parliament and of the Council, and repealing Council Regulations (EC) No 894/97, (EC) No 850/98, (EC) No 2549/2000, (EC) No 254/2002, (EC) No 812/2004 and (EC) No 2187/2005, OJ L 198, 25.7.2019, p. 105.

[34] Article 33 of the Regulation on technical measures contains amendments to the Fisheries Control Regulation. Actually, the approach to automatic size or sex grading equipment for certain fish species is set out by Article 54 c of the Fisheries Control Regulation, as amended by this Article 33.

[35] Regulation (EU) No 1379/2013 of the European Parliament and of the Council of 11 December 2013 on the common organisation of the markets in fishery and aquaculture products, amending Council Regulations (EC) No 1184/2006 and (EC) No 1224/2009 and repealing Council Regulation (EC) No 104/2000, OJ L 354, 28.12.2013, p. 1.

producer organisations, marketing standards, consumer information and certification (eco-labelling), competition rules and market information.

The COM in fishery and aquaculture products is an integral part of the CFP and should contribute towards the objectives of this policy. In this respect, AI instruments can provide valuable support tools for the achievement of these objectives for the marketing of fishery and aquaculture products in the Union market. The COM could contribute to improving the traceability of fishery products and grant access to clear and complete information by consumers (Article 5(e) and Article 7(c)). Contributions by AI could also be made for the fulfilment of measures that may be adopted by producer organisations in the fisheries and aquaculture sector to achieve Article 7 objectives. These include measures aimed at adjusting production to market requirements, channelling the supply and marketing of their members' products, promoting them, carrying out collective planning and management of their members' fishing activities, preventing and minimising unwanted catches by participating in the development and implementation of technical measures, managing the temporary storage of fishery products, etc. (Article 8). We consider that these AI instruments can facilitate the realisation by producer organisations of their production and marketing plans for the main species they market (Article 28), and also to improve the information reaching the consumer (Article 35-39).

Furthermore, under Article 42 of the COM, the Commission has launched the European Market Observatory for Fisheries and Aquaculture (EUMOFA), which is a market intelligence service consisting of a consolidated database of aggregated and harmonised data and a wide network of fisheries and aquaculture experts. Market intelligence is the information or data that an organisation obtains from the industry in which it operates to determine segmentation, penetration, opportunities, and existing metrics. We consider that AI systems can be appropriate tools to enhance the performance of these services.

2.1.7. Data Regulation in the fisheries sector

Regulation (EU) 2017/1004 of the European Parliament and of the Council on the establishment of a Union framework for the collection, management and use of data in the fisheries sector[36] (Data Collection Framework - DCF Regulation) is in line with the objectives of the CFP. The DCF Regulation aims to lay down rules on the collection, management and use of biological, environmental, technical and socio-economic data relating to the fisheries sector. The storage, processing and exchange of data should ensure compliance with the personal data protection obligations laid down in EU law[37]. The DCF Regulation is the main legal instrument establishing the rules on the collection, management, and use of fisheries data to support scientific advice for the CFP. Under Article 1(1) and Article 3(9) of the DCF Regulation, the term 'scientific data' includes biological, environmental, technical, and socioeconomic data in the fisheries sector. Where data necessary for fisheries management are collected under other EU legal acts (e.g., management plans, quota regulations and technical conservation measures), the Data Regulation in the fisheries sector only defines rules for the use and transmission of those data. Meaning that this Regulation is a framework regulation to all other EU laws requesting data for scientific purposes. All the rules on the processing, management and use of data under the DCF Regulation must comply with GDPR, Regulation (EU) 2018/1725 of the European

[36] Regulation (EU) 2017/1004 of the European Parliament and of the Council of 17 May 2017 on the establishment of a Union framework for the collection, management and use of data in the fisheries sector and support for scientific advice regarding the common fisheries policy and repealing Council Regulation (EC) No 199/2008, OJ L 157, 20.06.2017, p. 1.

[37] Directive 95/46/EC of the European Parliament and of the Council of 24 October 1995 on the protection of individuals with regard to the processing of personal data and on the free movement of such data (OJ L 281, 23.11.1995, p. 31); Regulation (EC) No 45/2001 of the European Parliament and of the Council of 18 December 2000 on the protection of individuals with regard to the processing of personal data by the Community institutions and bodies and on the free movement of such data (OJ L 8, 12.1.2001, p. 1).

Parliament and of the Council on the protection of personal data when processed by Union institutions[38] (Regulation on the protection of personal data when processed by Union institutions) and Regulation (EC) No 223/2009 of the European Parliament and of the Council on European statistics (Regulation on European statistics)[39].

The use of AI tools is a key opportunity to maximise the utility of data for sustainable fisheries management and for the assessment and monitoring of stocks and ecosystems, including data related to the LO (recital 29). Such a use could facilitate scientific advice to fisheries management that requires the processing of detailed data to address the needs of fisheries managers (recital 33), as well as ensure the timely availability of relevant data and respective methodologies to bodies having a scientific or management role in the scientific analysis of data in the fisheries sector and to any interested party (recital 34). Moreover, AI systems could be included among the appropriate procedures and electronic technologies employed as referred to in the Data Regulation in the fisheries sector, when it calls for the need for Member States to establish such procedures and technologies to ensure the availability of data and to cooperate with other Member States, the Commission, and end-users of scientific data to develop systems for data storage and exchange. These systems should provide for appropriate safeguards, such as a higher level of aggregation or anonymization of the data in case they include information on identified or identifiable natural persons, 'taking into account the purpose of the processing, the nature of the data and the potential risks related to the processing of personal data' (recital 35).

These AI tools are well fitted to operate with multiple data types obtained from the fisheries sector. In this regard, Article 3 of the DCF Regulation defines concepts such as 'primary data', 'metadata', 'detailed data' or 'aggregated data'. They can be useful in operations in relation to biological data on target and non-target stocks including bycatches, data to assess the impact of Union fishing activities on the marine ecosystem in Union waters and beyond, data on the activity of Union fishing vessels in Union waters and beyond, including levels of fishing and fishing effort and the capacity of the Union fleet (Article 5). They can also be useful tools in Member States' national work plans for establishing data sources, procedures and methods for their collection and processing into data sets that can then be provided to end-users of scientific data (Article 6(f)). These AI procedures may be present in the process of data collection (Article 12), data management (Article 13 and Article 14) and, above all, data use (Articles 15).

The collection, management of data, and making it available to end-users, is an obligation for Member States. They are responsible for data storage, protection of confidentiality, and completeness and quality of the data (Article 25 of CFP Framework Regulation, and Article 2(4), Article 13 and Article 14 of DCF Regulation). Thus, according to Article 25 of CFP Framework Regulation, such data is needed to enable the assessment of the state of exploited marine biological resources, the level of fishing and the impact that fishing activities have on the marine biological resources and ecosystems, and the socio-economic performance of the fisheries, aquaculture, and processing sectors within and outside Union waters. Fisheries data are to be made available to bodies with a research or management role in the scientific analysis of data in the fisheries sector, except where protection and confidentiality are required under applicable EU law. By 'scientific bodies' the regulation refers mainly to the Scientific

[38] Regulation (EU) 2018/1725 of the European Parliament and of the Council of 23 October 2018 on the protection of natural persons with regard to the processing of personal data by the Union institutions, bodies and agencies and on the free movement of such data, and repealing Regulation (EC) No 45/2001 and Decision No 1247/2002/EC, OJ L 295, 21.11.2018, p.39.

[39] Regulation (EC) No 223/2009 of the European Parliament and of the Council of 11 March 2009 on European statistics and repealing Regulation (EC, Euratom) No 1101/2008 of the European Parliament and of the Council on the transmission of data subject to statistical confidentiality to the Statistical Office of the European Communities, Council Regulation (EC) No 322/97 on Community Statistics, and Council Decision 89/382/EEC, Euratom establishing a Committee on the Statistical Programmes of the European Communities, OJ L 87, 31.3.2009, p. 164.

Technical Economic Committee on Fisheries (STECF), which is the scientific body of the Commission for fisheries matters. However other relevant scientific bodies (e.g., the International Council for the Exploitation of the Sea (ICES)) and the scientific committees of RFMOs are also considered to be bounded by the rules of data protection. As an example, ICES data policy establishes that data is put at the service of the scientific community and is publicly available, with some exceptions such as commercial, catch and VMS and logbook data.

2.1.8. European Maritime, Fisheries and Aquaculture Fund Regulation

The European Maritime, Fisheries and Aquaculture Fund (EMFAF) Regulation is an EU fund that will be active between 2021 and 2027. It channels financial resources from the EU budget to support the CFP, the EU maritime policy and the EU's agenda for international ocean governance. It provides financial support for the development of innovative projects ensuring that aquatic and maritime resources are used in a sustainable manner. Its objectives are, among others, to support innovation and investment in low-impact, selective, climate-resilient, and low-carbon fishing practices, and techniques (recital 20), which, in our view, would also include AI systems.

Similarly, the EMFAF Regulation should support innovation and investments that contribute to the full implementation of the LO, as well as the development and implementation of conservation measures that contribute to selectivity. In this respect, it considers that it would be appropriate, *inter alia*, to grant investments and aid to selective fishing gear with a higher rate than that applied to other operations (recital 22). In this regard, we consider that AI tools have a huge potential to contribute to selective fishing gear development and improvement. In addition, the EMFAF will promote innovation and investments on board Union fishing vessels, including support aimed at improving the quality of catches (recital 23), which is one of the purposes of several AI schemes. The EMFAF Regulation recognises that the success of the CFP depends on the availability of scientific advice for fisheries management and therefore on the availability of fisheries data (recital 24), and again AI tools can certainly contribute to reliable and comprehensive marine data.

Moreover, when examining national projects eligible for EMFAF funding, the Regulation states that, *inter alia*, their contribution to the digital transition shall be taken into account (recital 51), and reiterates this in its articles, stating that the Commission, when assessing national programmes, shall take particular account of the optimisation of the programme's contribution to the objectives of resilience, ecological transition and digital transition, in particular through a wide range of innovative solutions (Article 8(5)(a)). It is also stated that the EMFAF will support interventions that contribute to reliable data for knowledge-based decision-making (Article 14(d)). Along these lines, it also states that the EMFAF may support research and innovation programmes in fisheries and aquaculture, and the collection, management, use and processing of biological, environmental, technical, and socio-economic data in the fisheries sector (Article 23(1)). In this sense, AI systems are included in the digital transition process, which contribute to data analysing and enhance knowledge-based decision-making processes.

2.1.9. Marine Strategy Framework Directive

The MSFD represents a major contribution to the conservation, protection, and restoration of marine ecosystems. It includes reduction and minimisation of pollution, aimed at achieving good environmental status for EU waters by 2020. According to this normative act, the EU Member States should progressively work towards achieving good environmental status to ensure that the seas are clean, healthy, and productive, and to reduce the impact of human activities on marine ecosystems. Among the main objectives of the MSFD, reference should be made to guaranteeing that pressures from human activities are kept at levels compatible with good environmental status, and to keep commercially exploited fish stocks, as well as those of other marine animals, stable within safe biological limits, to ensure their long-term sustainability.

It should be underlined that the MFSD dates from 2008. Therefore, references to AI technology are logically absent, but it provides for the Commission to be empowered to adapt it to technical and scientific progress (recital 47). The authors of this study consider that the use of AI tools can be useful in the preparation of the Marine Strategies referred to in Chapter II of this Directive, both in their assessment phase (Article 8), in the determination of good environmental status (Article 9), and in the establishment and implementation of monitoring programmes (Article 11). Additionally, they might also be appropriate instruments to reinforce the monitoring programmes referred to in Annex V, or the programmes of measures indicated in Annex VI. In any case, these issues related to the use of AI tools may be taken into consideration during the legislative debates on the revision of the MSFD, which should be undertaken by 15 July 2023, as provided for in Article 23 of the Directive.

2.1.10. Directive on marine equipment

Finally, although it is a regulatory act within the framework of the EU Transport Policy, we refer to the Directive on marine equipment as it also affects fishing vessels in terms of safety. This Directive seeks to enhance safety at sea as well as 'to prevent marine pollution through the uniform application of the relevant international instruments relating to marine equipment to be placed on board EU ships, and to ensure the free movement of such equipment within the Union. As AI systems may be components of marine equipment whose use or installation on board ships is deemed necessary to enhance maritime safety, it could be understood that equipment legislation would apply to them. As mentioned before, this possibility is expressly included in the AIA proposal by virtue of Article 78, which contains an amendment to Article 8 of this Directive. Although these requirements refer to high-risk systems which, as will be seen below, do not affect fishing activities, we think it is useful to refer to this situation.

2.1.11. Final considerations

The most relevant EU fisheries legislation analysed in this part of the study (see summary table 1) shows how these provisions facilitate the use of AI applied to different fisheries activities. No provisions that would conflict with the AIA proposal were found. The authors consider that concerns for the respect of fundamental rights, the protection of European consumers, product safety and liability are already present in fisheries legislation and are reinforced with the AIA proposal text. The authors also consider that the fisheries legislation currently in the process of legislative revision or soon to undergo some could and should include references to AI systems in those recitals where digital transformation and new technologies are mentioned. This would significantly contribute to greater legal certainty and transparency for consumers and economic operators in relation to the use of AI systems in the fisheries sector. As indicated by the CJEU on numerous occasions, EU legislation '[…] must be certain and its application foreseeable by individuals. The principle of legal certainty requires that every measure of the institutions having legal effects must be clear and precise […]'[40]. Additionally, transparency, as a general principle governing the functioning of the EU institutional system, would help to make EU regulatory provisions more comprehensible, including those relating to AI in fisheries.

[40] Judgment of the Court of First Instance (Fourth Chamber) of 22 January 1997 in the Case Opel Austria GmbH v Council of the European Union, T-115/94, ECLI:EU: T:1997:3, punto 124.

Table 1: Non-exhaustive summary of the recitals and articles of the most relevant EU fisheries legislation containing elements making the use of AI systems possible

EU law	Recital	Article
CFP Framework Regulation	25, 46, 49, 51, 60, 64	2(1), 3I, 7(1)(c), 7(1)(d), 7(1)(h), 7(2)(b), 21-25, 28-33, 31, 36-42
Fisheries Control Regulation	14-16, 18, 20, 28, 48	5(3), 6-13, 15, 17-21, 23, 26-37, 47-49, 58, 66-67, 109(1), 109(2)(b), 110, 112-116,
Regulation on the sustainable management of external fishing fleets	14, 27-28, 33-34	39-44
IUU Regulation	7, 9, 21, 26-29	8, 12, 14
Regulation on the conservation of fisheries resources and the protection of marine ecosystems through technical measures	22, 30, 33	3, 6, 8-9, 13-14, 23, 33
Regulation on the COM in seafood products		5(e), 7(c), 8, 35-39, 42
Data Regulation in the fisheries sector	2(4), 13, 14, 29, 33-35	1(1), 3, 5, 6(f), 12-21
EMFAF	22-24, 51	8(5)(a), 14(d), 23(1)
Marine Strategy Framework Directive	47	9, 11, 23

Source: Gabriela A. Oanta and José Manuel Sobrino Heredia.

2.2. EU legislation ensuring the protection of citizens and business rights in AI systems

This section examines the main EU legislation that addresses ethical, legal, and economic concerns, mainly related to the risks to human rights and fundamental freedoms such as the right to privacy, data protection and discrimination rules. The main concerns related to the use of AI are related to the application of rules designed to protect fundamental rights (including personal data, privacy protection and non-discrimination), as well as safety and liability-related issues[41]. Developers and deployers of AI in the fishery sector are already subject to European legislation on fundamental rights, consumer protection, product safety[42] and liability[43] rules.

2.2.1. Legislation laying down fundamental rights and EU values

The primary sources in the EU legal system regarding EU values and fundamental rights are the Treaty on the European Union (TEU), the Treaty on the Functioning of the European Union (TFEU) (both being the 'EU Treaties'[44]), and the EU Charter on Fundamental Rights[45] (Charter). It is worth mentioning that

[41] White Paper on Artificial Intelligence – A European approach to excellence and trust, COM(2020) 65 final, Brussels, 19.2.2020.

[42] Directive 2001/95/EC of the European Parliament and of the Council of 3 December 2001 on general product safety (OJ L 11, 15.1.2002, p. 4); Directive 2006/42/EC of the European Parliament and of the Council of 17 May 2006 on machinery, and amending Directive 95/16/EC (recast) (OJ L 157, 9.6.2006, p. 24); and Directive 2014/53/EU of the European Parliament and of the Council of 16 April 2014 on the harmonization of the laws of Member States relating to the making available on the market of radio equipment and repealing Directive 1999/5/EC (OJ L 153, 22.5.2014, p. 62).

[43] Council Directive 85/374/EEC of 25 July 1985 on the approximation of the laws, regulations and administrative provisions on the Member States concerning liability for defective products (OJ L 210, 7.8.1985, p. 29). This Directive was amended by Directive 1999/34/EC as to include agriculture and fisheries products. See: Directive 1999/34/EC of the European Parliament and of the Council of 10 May 1999 amending Council Directive 85/374/EEC on the approximation of the laws, regulations and administrative provisions of the Member States concerning liability for defective products (OJ L 141, 4.6.1999, p. 20).

[44] Consolidated version of the Treaty on European Union (OJ C 326, 26.10.2012, p. 13) and consolidated version of the Treaty on the Functioning of the European Union (OJ C 202, 7.6.2016, p. 1).

[45] OJ C 364, 18.12.2000, p. 1

Article 2 TEU states that the Union is founded on the values of respect for human dignity, freedom, democracy, equality, the rule of law and respect for human rights, including the rights of persons belonging to minorities. The TFEU compels the Union to eliminate inequalities and promote equality (Article 8), to combat discrimination (Article 10), and it recognizes the right of everyone to the protection of personal data concerning them (Article 16). The Charter recognizes the right to privacy (Article 7) and of the protection to personal data (Article 8). Since 2009, according to Article 6 TEU, the Charter has the same legal status as the EU Treaties, being primary EU law on which EU legislation is based. European institutions must comply with it in all their actions, and EU Member States must comply with it when they implement EU law. National courts can apply the Charter in cases where EU law is implemented and is relevant for the final judgement.

2.2.2. Legislation related to the protection of personal data

Everyone has the right to the protection, access and rectification of their collected personal data (Article 8 of the Charter and Article 16 TFEU). The main EU legislation dealing with the protection of personal data are: GDPR ; Regulation on the protection of personal data when processed by the EU institutions; Directive (EU) 2016/680 of the European Parliament and of the Council on the protection of natural persons with regard to the processing of personal data by competent authorities for the purposes of the prevention, investigation, detection or prosecution of criminal offenses or the execution of criminal penalties, and on the free movement of such data[46] (Data Protection Law Enforcement Directive); and Directive 2002/58 of the European Parliament and of the Council on privacy and electronic communications[47] (Directive on privacy and electronic communications). These legal instruments are key in the Communication published by the European Commission on 21 November 2018, entitled 'European Commission Digital Strategy: A digitally transformed, user-focused and data-driven Commission'[48] (European Commission Digital Strategy), to create an ecosystem of trust by ensuring the protection of the fundamental right to personal data protection and the flow of data among Member States.

The GDPR protects the fundamental rights and freedoms of natural persons, and in particular their right to the protection of personal data, and on the free movement of such data (Article 1), when these data are processed wholly or partly by automated means or other means which form part of a filing system (Article 2). Personal data is defined as any information relating to an identified or identifiable natural person[49]. EU Member States must ensure in their national laws that personal data are processed in accordance with the principles of lawfulness, fairness, and transparency, processed only for specified and explicit purposes, be limited to what is necessary and kept safe and only for as long as necessary (Article 5). Although AI is not explicitly mentioned in the GDPR, many of its provisions are relevant to its use. However, the GDPR provisions are often vague and open-ended, and therefore there is a need to further refine them[50].

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[46] Directive (EU) 2016/680 of the European Parliament and of the Council of 27 of April 2016 on the protection of natural persons with regard to the processing of personal data by competent authorities for the purposes of the prevention, investigation, detection or prosecution of criminal offenses or the execution of criminal penalties, and on the free movement of such data, and repealing Council Framework Decision 2008/977/JHA, OJ L 119, 4.5.2016, p. 1.

[47] Directive 2002/58 of the European Parliament and of the Council of 12 July 2002 concerning the processing of personal data and the protection of privacy in the electronic communications sector, OJ L 201, 31.7.2002, p. 37.

[48] C(2018) 7118 final, Brussels, 21.11.2018.

[49] Article 4 GDPR sets out: 'An identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person'.

[50] EPRS, The impact of the General Data Protection Regulation on artificial intelligence. European Parliament Research Service. Scientific Foresight Unit, (STOA). PE 641.530 June 2020.

Regulations on the protection of personal data when processed by the EU institutions establish the rules applicable to the processing of personal data by the Union institutions, bodies, offices and agencies. It creates the European Data Protection Supervisor (EDPS), which is an independent EU body responsible for monitoring the application of data protection rules within the EU institutions and for investigating complaints. When citizens data is used by criminal law enforcement authorities for law enforcement purposes, the Data Protection Law Enforcement Directive ensures the right to data protection[51]. The Directive on privacy and electronic communications[52] complements the General Data Protection Regulation. This Directive harmonizes the provisions of the Member States required to ensure an equivalent level of protection of fundamental rights and freedoms. It applies to the processing of personal data in connection with publicly available electronic communications services in public communication networks in the EU (Article 1).

2.2.3. Legislation dealing with data

The European Data Strategy acknowledges that access to data and the ability to use it are essential conditions for innovation and growth. This strategy aims to create a single market for data to allow its flow freely within the EU and across sectors for the benefit of all. The legislative instruments supporting this strategy are the Proposal for a Regulation of the European Parliament and of the Council on European Data Governance (proposal for a Data Governance Act)[53], the Directive (EU) 2019/1024 of the European Parliament and of the Council of 20 June 2019 on open data and the re-use of public sector information (Open Data Directive)[54] and Proposal for a Regulation of the European Parliament and of the Council on harmonised rules on fair access to and use of data (COM(2022) 68 final)[55] (Data Act).

The commission adopted the proposal for a Data Governance Act that reached a political agreement by the Parliament and Council in December 2021 and will be soon voted in plenary in March 2022. The objective for the proposal for a Data Governance Act is to create trustworthy data-sharing systems, so that more data (personal and non-personal) is available and shared for the benefit of all. Data governance refers to a set of rules and means to use data, for example through sharing mechanisms, agreements, and technical standards. It includes rules to share data in a secure manner, included through trusted third parties ('data intermediaries'), and supervised by public authorities. When public data subject to rights of others is shared (e.g., data subject to data protection, intellectual property, containing trade secrets or commercially sensitive information), Member States must ensure compliance with the General Data Protection Regulation and respect for privacy and confidentiality. There are practices developed to protect privacy and confidentiality such as using 'anonymization' or legally binding confidentiality agreements to be signed by the re-user. The proposal includes measures to facilitate data to be used across sectors (so called 'European data spaces'), such as the agricultural sector, where fisheries are not included. The Open Data Directive lays down rules for the re-use of public sector information and provides common rules for a European market for government held data. Within the framework of the European Strategy for Data, the Commission adopted the proposal for a

[51] Directive (EU) 2016/680 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data by competent authorities for the purposes of the prevention, investigation, detection or prosecution of criminal offences or the execution of criminal penalties, and on the free movement of such data, and repealing Council Framework Decision 2008/977/JHA (OJ L 119, 4.5.2016, p. 89).

[52] Directive 2002/58/EC of the European Parliament and of the Council of 12 July 2002 concerning the processing of personal data and the protection of privacy in the electronic communications sector (Directive on privacy and electronic communications) (OJ L 201, 31.7.2002, p. 37).

[53] COM(2020) 767 final, Brussels, 25.11.2020.

[54] OJ L 172, 26.6.2019, p. 56.

[55] Proposal for a Regulation of the European Parliament and of the Council on harmonised rules on fair access to and use of data (Data Act), COM (2022) 68 final, 23.2.2022.

'Data Act' including the review of Directive 96/9/EC on the legal protection of databases. This legal instrument aims to encourage data sharing among businesses, and between business and governance.

2.2.4. AIA proposal foundations, including safety and liability issues

The White Paper on AI[56] sets out policy options on how to promote the uptake of AI and address the risks associated with certain uses of this technology. These options where considered in the AIA proposal aim to develop an ecosystem of trust by proposing a legal framework for trustworthy AI. The Report from the European Commission to the European Parliament, the Council and the European Economic and Social Committee on the Safety and Liability Implications of Artificial Intelligence, the Internet of Things and Robotics[57] accompanying the White Paper on AI identifies and examines the broader implications and potential gaps in the liability and safety frameworks for AI. Consumers expect the same level of safety and respect of their rights whether a product relies on AI or not. However, the technical complexity of AI can create uncertainty about the application and enforcement of safety legislation including cybersecurity, applications in critical infrastructures, or malicious use. The report concludes that the current product safety legislation contains several gaps that need to be addressed.

New challenges in terms of liability also need to be tackled to ensure the same level of protection compared to victims of traditional technologies[58]. In line with the European Parliament resolution[59] on the civil liability regimen for AI, the rise of AI systems presents a significant challenge for the existing liability frameworks. Using AI-systems could lead to situations in which the opacity, autonomy and the multitude of actors who intervene in their lifecycle make it expensive or impossible to identify who was in control of the risk of using the AI-system in question or which code or input caused the harmful operation. Moreover, the mere operation of an autonomous AI-system should not be a sufficient ground for admitting the liability claim. As a result, there might be liability cases in which the allocation of liability could be unfair or inefficient, or in which a person who suffers harm or damage caused by an AI-system cannot prove the fault of the producer, of an interfering third party or of the operator and ends up without compensation. This creates legal uncertainty for businesses and makes it difficult for consumers and other injured parties to get compensation for damage caused by products and services that use these technologies. The European Commission plans to revise legislation on product safety and on liability issues related to new technologies, including AI systems in 2022. It is also expected to adopt the Directive on civil liability to adapt the rules to a digital age and AI, during the third quarter of 2022. This initiative is part of the Commission approach to developing an ecosystem of trust in the use of AI and it will complement the proposal for an AIA and revised safety legislation such as the Machinery Regulation and General Product Safety Directive.

The AIA proposal, which is part of a package of measures that addresses problems posed in relation to the development and use of AI, aims at providing enough protection of fundamental rights and safety, and the creation of a single market of trustworthy AI systems. It includes a broad definition of AI systems, as techniques and approaches including ML approaches, logic and knowledge-based approaches and statistical approaches. The objective of the proposal is fivefold:

- To harmonize the rules for placing AI systems on the EU market.
- To prohibit certain AI practices (that may infringe certain fundamental rights).
- To require specific conditions for high-risk AI systems and the operators of such systems.

56 COM(2020) 65 final.

57 COM(2020) 64 final, Brussels, 19.2.2020.

58 European Commission, Directorate-General for Justice and Consumers, Liability for artificial intelligence and other emerging digital technologies, Publications Office, 2019.

59 European Parliament resolution of 20 October 2020 on civil liability regimen for artificial intelligence (2020/2014(INL)), P9_TA (2020)0276.

- To harmonize transparency rules for AI systems intended to interact with natural persons.
- To lay down rules for market monitoring and surveillance.

The AIA proposal requires full consistency with the Charter, and Union legislation on data protection, consumer protection and competition law. The proposed rules will be enforced through a governance system at the Member State level, and a cooperation mechanism at Union level with the establishment of a European Artificial Intelligence Board. The AIA proposal also significantly strengthens the Union's role to help shape global norms and standards and promote trustworthy AI that is consistent with Union values and interests.

Regarding the application of these rules to the fisheries sector, *a priori*, when algorithms use biological, environmental, and technical data for the purposes of fisheries management and control, the rights of persons and businesses are not likely to be affected. However, the disclosure of catches taken by a specific vessel in a specific area and date could be contrary to confidentiality of professional data, commercial secrecy and generate unfair competition. For this reason, when Member States collect and transmit these data, they are under the obligation to make sure that these are properly protected. The current practice for data publicly shown is to aggregate it in a way that it is not possible to directly identify which individual vessels have generated the data or the specific contribution of a particular vessel to the data. Although aggregation of data is necessary to protect certain rights, the way the data are aggregated may in turn create limitations for the algorithm applications or for some scientific and management needs. This a point that deserves special consideration since it can be a technical barrier for an efficient use of AI in the fisheries sector.

Socioeconomic data is provided by Member States to the Commission and other end-users who are bound by the rules on data protection and confidentiality. The purposes for which these data are collected and processed is to contribute to the overall objective of the CFP to sustainably manage the exploitation of fisheries resources. As discussed in the analysis of fisheries legislation, AI systems in the fisheries are not to use socioeconomic data with the aim to influence human behaviour, or to affect the rights of individuals in a way that undermine fundamental rights and freedoms of the person. Thus, as a general statement, the use of AI techniques and algorithms processing personal and business data in the fisheries sector should not create any additional risks related to the protection of personal data and confidentiality rules.

2.3. The jurisprudence of the Court of Justice of the EU on the use of AI

The CJEU as the judicial authority of the EU by virtue of Article 19 TEU, in cooperation with the judicial bodies of the EU Member States, ensures the uniform application and interpretation of EU law. As it is responsible for reviewing the legality of the acts adopted by the European institutions, ensuring that the Member States comply with the obligations laid down in the TEU and the TFEU, and interpreting EU law at the request of national judges. The CJEU has jurisdiction to examine disputes to which the Member States, the European institutions, business companies and individuals can be parties in relation to the interpretation and application of the EU legal order. The CJEU's jurisdiction is broad, and the Court has been involved in very few cases on issues that directly or indirectly might relate to potential uses of AI in the field of fisheries.

2.3.1. Case on commercial discrimination using AI

References to ML, a common AI systems technique, were found in the judgment of the General Court of 10 November 2021 in the case Google and Alphabet v Commission (Google Shopping)[60]. The applicant brought an action for annulment by virtue of Article 263 TFEU against the Commission Decision C(2017) 4444 final of 27 June 2017 adopted in relation to abuse of dominant position occasioned by online general search services and specialised product search services. Thus, the Commission mentioned ML twice to demonstrate to the General Court the abusive nature of the practices of Google LLC. The Commission noted, quoting numerous statements in that regard, that traffic led to ML effects, thereby improving the relevance of the search results and thus the usefulness of the comparison-shopping service offered to internet users (paragraph 64). Later on, the Commission 'explained that the traffic increased the relevance of specialised search results and in particular the freshness and breadth of the offering of comparison shopping services by enhancing their ability to convince merchants to provide them with data about their products [...] that it generated revenue either via commissions paid by merchants or online advertising [...] and that it provided information about user behaviour, which improved the relevance and usefulness of results, including through ML effects [...] experiments or the suggestion of other search terms that might be of interest for users' (paragraph 170). An appeal has now been brought against this judgment before the Court of Justice [61].

This case shows that, like many other technological developments, AI can give a competitive advantage to companies. However, that in fisheries a technological provider can exclude others from the market is unlikely in the sort to medium term given the large history of non-monopolistic competition and considering that these companies mostly specialise on hardware, and not add-ons like AI.

2.3.2. Case on illegal mechanical device for fish classification

A Court of Justice case was found where an illegal mechanical fish classification device was used. Despite this being a mechanical device not fitted with an AI system, in the authors' opinion the same types of procedures could be applied to AI systems. These classification devices can be very useful to speed up the value chain process by separation of fish sizes during fishing trips, but these devices can also foment illegal discards at sea of less profitable smaller sizes. In its judgment of 11 February 2021 in Case K.M.[62], the Court of Justice ruled on the reference for a preliminary ruling received from the Irish Court of Appeal under Article 267 TFEU. This request had been made in the context of criminal proceedings brought against K.M., the master of a fishing vessel, for having on board his fishing vessel an automatic size-sorting equipment for herring, mackerel, and horse mackerel, which was not installed or located on the vessel in such a way that freezing was carried out immediately to prevent returning marine organisms to sea.

Both the EU legal order legislation and Ireland's legislation[63] prohibit the on-board possession and use of such equipment. At the time of the commission of the acts, which gave rise to the case before the Irish courts, Article 32(1) of the Council Regulation (EC) No 850/98 of 30 March 1998 for the conservation of fishery resources through technical measures for the protection of juveniles of marine organisms[64] was the relevant provision to be applied. Years later, this Regulation was repealed by the Regulation on technical measures. Additionally, Article 33 of Regulation on technical measures, which also

60 Judgment of the General Court of 10 November 2021, Google and Alphabet v Commission (Google Shopping), T-612/17, ECLI:EU:T:2021:763.
61 It is about the case C-48/22 P.
62 Judgment of the Court of Justice of 11 February 2021, K.M., C-77/20, ECLI:EU:C:2021:112.
63 Article 14(3) of the Sea Fisheries and Maritime Jurisdiction Act 2006.
64 OJ L 125, 27.4.1998, p. 1.

introduced amendments to the FCR, introduced Article 54c on restrictions on the use of automatic grading equipment which is only permitted if: a) the vessel does not simultaneously carry or use on board either towed gear of mesh size less than 70 mm or one or more purse seines or similar fishing gear; or (b) the whole of the catch which may be lawfully retained on board: (i) is stored in a frozen state, (ii) the graded fish are frozen immediately after grading and no graded fish are returned to the sea; and, (iii) the equipment is installed and located on the vessel in such a way as to ensure immediate freezing and to not allow the return of marine species to the sea.

The Court of Justice was asked whether Article 89 and Article 90 of FCR, read in the light of the principle of proportionality enshrined in Article 49(3) of the Charter, were to be interpreted as precluding a national provision which, in order to penalise an infringement of Article 32 of Regulation No 850/98, provided for the imposition of a fine and the mandatory confiscation of prohibited or non-compliant catches and fishing gear found on board the vessel concerned (paragraph 25). Under Article 89 and Article 90 of FCR, Member States have to ensure that appropriate measures are taken to sanction infringements of the CFP rules. These provisions do not impose specific sanctions, but they stablish certain criteria that Member States must consider, and the principle that such sanctions must be effective, proportionate, and dissuasive (paragraph 30). According to settled jurisprudence, in the absence of harmonisation of EU legislation in the field of applicable sanctions, Member States remain competent to lay down the sanctions they consider appropriate. However, they have the obligation to exercise this competence in compliance with EU legal order and the general principles of EU law and, consequently, in accordance with the principle of proportionality[65]. The Court of Justice found that the mandatory confiscation of prohibited or non-compliant catches and fishing gear may deter the persons concerned from infringing the prohibition on sorting equipment, laid down in Article 32(1) of Regulation No 850/98, by depriving them of the illegally obtained benefits which they could otherwise enjoy, and of the possibility of continuing to use such equipment (paragraph 44).

This may be an important judgment since AI systems developers will need to ensure their designed tools do not enable (or make difficult) their misuse to avoid potential bans on their methodologies. On the other hand, as shown in this study in later chapters, various AI systems are being developed with the aim of avoiding discards or bycatch before the fishing event happens by forecasting and observing the fish at sea to prevent this problem.

2.3.3. Other cases where the term AI is mentioned

The term 'AI' has been mentioned in other cases brought before the CJEU. Thus, in its judgment of 15 December 2021 in Case Breyer/REA, the General Court noted that 'questions of principle on the use of artificial intelligence' were being raised in this case[66]. However, it does not develop this idea. In addition, in five other cases in whose opinions the respective Advocate General used the term 'AI', namely:

- Opinion of Advocate General delivered on 15 April 2021 in the case KRONE – Verlag (footnotes 10 and 16)[67].
- Opinion of Advocate General delivered on 17 December 2020 in the case The Software Incubator (footnote 29)[68].

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65 Among other judgments, see: judgment of the Court of Justice of 16 July 2015, Chmielewski, C-178/03, ECLI:EU:C:2015:475, paragraph 21.

66 Judgment of the General Court of 15 December 2021, Breyer/REA, T-158/19, ECLI:EU:T:2021:902, paragraph 182.

67 C-65/20, ECLI:EU:C:2021:298.

68 C-410/19, ECLI:EU:C:2020:1061.

- Opinion of Advocate General delivered on 15 July 2021 in the case Poland v Parliament and Council (footnote 74)[69].
- Opinion of Advocate General delivered on 11 March 2020 in the case Blackrock Investment Management (UK) (paragraph 1)[70].
- Opinion of Advocate General delivered on 9 February 2017 in the case Lahorgue (paragraph 2) [71].

These opinions refer to AI as one of technologies, among other, that can change the work in several sectors and bring new challenges. However, these are not considered exclusively to be AI and no express link has been identified between the use of this term in these cases and the field of fisheries.

2.4. State of legislation of third countries on the use of AI: Australia, New Zealand, United States and China

FAOLEX, the FAO's database of legislative and policy documents, was consulted by employing the searching terms 'artificial intelligence' and 'machine learning' in combination with 'fisheries', but no results were found. Nonetheless, in some countries such as Australia, New Zealand, and the United States of America (US) the use of AI in fisheries management is being considered and explicitly mentioned in some official government documents (Fisheries New Zealand, 2021). An example is the 'Consultation of the wider rollout of on-board cameras' launched by the Ministry of Primary Industries (MPI) of New Zealand in 2021 (Fisheries New Zealand, 2021). The MPI states that 'alongside the introduction of electronic catch and position reporting, on-board cameras will support better, more nimble decision-making and as technology and AI develops there will be further transformative opportunities'.

Since 2014 the Australian Fisheries Management Authority (AFMA) started to implement EM in several pelagic fisheries targeting tunas and sharks, and in small pelagic fisheries (AFMA, 2019). The goals of the implementation were to collect real time and accurate data on fishing activities such as catches, discards, bycatch, and interaction with protected species and to monitor compliance with fishing regulations (AFMA, 2020), but AI is not yet incorporated in these systems (see chapter 3 for literature review). AFMA employs EM data to fulfil its functions in accordance with the Fisheries Management Act of 1991[72] which allows use of EM. AFMA complies with requirements on privacy and freedom of information as per the Freedom of Information Act of 1982[73], which applies to data in written or visual form (AFMA, 2020).

In New Zealand, EM systems use started in November 2019 with a group of 28 vessels operating off the west coast of the North Island (Fisheries New Zealand, 2019) to verify interactions with endangered Māui dolphins. There are specific regulations concerning the use EM for control purposes[74]. Release of fisheries information coming from EM is in turn regulated by the Official Information Act[75] and Privacy Act[76] obligations.

[69] C-401/19, ECLI:EU:C:2021:613.
[70] C-231/19, ECLI:EU:C:2020:196.
[71] C-99/16, ECLI:EU:C:2017:107.
[72] Fisheries Management Act 1991. No. 162, 1991. Compilation date: 26 September 2021. Includes amendments up to: Act No. 32, 2021. Registered: 15 of November 2021.
[73] Freedom of Information Act 1982. No. 3, 1982. Compilation No. 105. Compilation date: 23 January 2022. Registered: 7 February 2022.
[74] Fisheries (Electronic Monitoring on Vessels) Regulations 2017 (LI 2017/156). Version as at 28 October 2021.
[75] Official Information Act 1982. Version as at 28 October 2021. Public Act: 1982 No 156. Date of assent: 17 December 1982.
[76] Privacy Act 2020. Version as at 28 October 2021. Public Act: 2020 No 31. Date of assent: 30 June 2020.

In the US, AI is not currently applied in fisheries management and control. Nevertheless, EM systems are being widely applied and AI is being seriously considered to automatically process video recordings[77]. There are specific regulations in place for EM (EDF, 2020). In turn, data confidentiality issues are dealt with in accordance with fisheries and fisheries related regulations i.e., Magnuson-Stevens Fisheries and Conservation act[78], and the Marine Mammal Protection Act[79] respectively. Data confidentiality is also affected by general regulation such as the Freedom of Information Act[80].

Finally, the Chinese government aims to become a world leader in both the development and use of AI by 2030. In 2015, it put forward the 'Made in China 2025 plan', and in 2017 China's State Council released the 'New Generation Artificial Intelligence Development Plan', expressing the national ambitions to lead the global AI industry by 2030. The term 'AI' is not well-defined in China's policy and legislation. Many laws govern AI in the sense that China's legal and administrative institutions already govern every industry and individual conducts. It is unclear to what extent the use of AI affects these existing laws (Lucero, 2019). Although this document makes no specific reference to fisheries, it will likely apply to this industry in some way as China has one of the most powerful fishing fleets worldwide, especially its distant water fleet (DWF) operating in the high seas.

77 https://blogs.edf.org/edfish/2021/03/01/computer-assisted-monitoring-technologies-are-set-to-revolutionize-fisheries/

78 Magnuson-Stevens Fishery Conservation and Management Act. As Amended Through January 12, 2007.

79 The Marine Mammal Protection Act of 1972 as amended through 2018.

80 The Freedom of Information Act. 5 U.S.C. § 552, as amended by public law No 104-231, 110 STAT. 3048.

3. ANALYSIS OF THE CURRENT AND POTENTIAL USE OF AI TECHNIQUES AND APPROACHES IN THE FISHERIES SECTOR

KEY FINDINGS

- The Artificial Intelligence Act (AIA) proposal classifies AI techniques and approaches in three groups: a) machine learning (ML), b) logic- and knowledge-based approaches and c) statistical approaches, Bayesian estimation, search and optimization methods.
- ML approaches have been mainly used to automatize sample processing to infer the biological parameters for species status assessments and their management.
- ML has been applied in image analysis and acoustic data to count and measure organisms.
- Recently AI research on catch monitoring has increased, especially for classification by species and sizes.
- ML is being applied to automatically classify or determine fishers' behaviour based on monitoring systems data.
- Knowledge-based and expert systems have been applied for early warning systems and Marine Spatial Planning using ML and statistical approaches.
- Traditional rule-based expert systems have been mainly applied in data-limited situations.
- Statistical approaches, Bayesian estimation, and search and optimization methods are not traditionally considered AI, but can be integrated into AI systems.
- Some of the statistical uses identified are applied for vessel route optimization, stock assessments and species distribution models.
- Fishing vessels could improve energy efficiency and reduce CO2 emissions combining all the above AI methodologies to locate target fish more accurately with less fuel.
- Scientists highlight the current use and potential of AI in sample processing and data analysis for fisheries ecology and management purposes.
- Data collection and its processing could improve significantly with AI if collaboration between fishers and scientists from various fields increases.
- There is a lack of experts (and incentives) with multidisciplinary skills that combine computing, marine and legal knowledge.
- European Commission experts highlight the potential of AI to better implement fishing regulation compliance control, improve marine spatial utilization, increase the amount and availability velocity of biological and socio-economic data and provide forecasts on production and consumption.
- NGOs consider that AI should be used in the framework of a long-term strategy embedded into an ecosystem-based management plan and not as an isolated tool.

In this chapter, firstly the main areas of fisheries science and management are described. Secondly, AI techniques, following the categorization of the AIA proposal, are explained highlighting their similarities and differences. Thirdly, a review of scientific publications focused on AI methods in fisheries shows the areas of fisheries science where AI techniques have been more broadly applied with an example of fuel reduction. Finally, opportunities and obstacles identified in stakeholders' consultation are summarised.

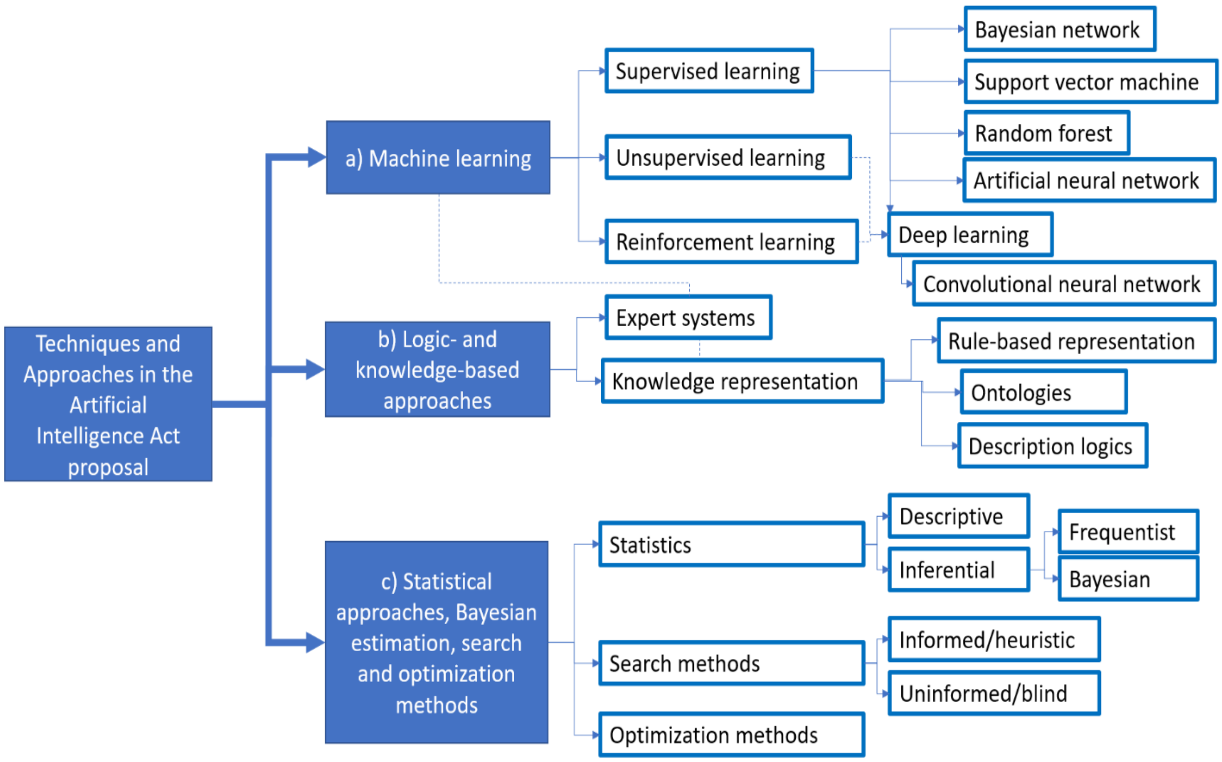
Fisheries is a multidisciplinary science traditionally drawing from disciplines such as oceanography, biology, ecology, population dynamics, statistics, economics, decision analysis and management. Nowadays, new disciplines are emerging such as computational biology, fisheries law and bio economics. For example, AI is increasingly being used in fisheries science. Modern fisheries management aims to produce sustainable biological, social, and economic benefits from renewable aquatic resources. Properly managed fisheries are considered a renewable resource since an annual surplus can be harvested without reducing future productivity. Consequently, a lot of the work of fisheries management focuses on building the biological and ecological understanding to estimate this surplus and defining rules for its harvesting. Another important activity of fisheries management is the monitoring control and surveillance for compliance with these rules and harvesting outcomes. Furthermore, it is also important for industry and society to know this surplus distribution and impact of other human activities in a broader ecosystem approach. ML and big data (Hu et al., 2014) have already shown their potential in marine sciences applied to fisheries forecasting (Fernandes et al., 2010), automatic classification of zooplankton samples (Fernandes et al., 2009; Uusitalo et al., 2016), and evaluation of ecosystem changes (Uusitalo et al., 2018; Maldonado et al., 2019). A transdisciplinary approach is needed that brings different domain experts, AI experts and policy and stakeholders' knowledge together to co-create fit-for-purpose systems beyond the state-of-the-art AI technology in more than one discipline simultaneously (Andonegi et al., 2011; Fernandes et al., 2013; Uusitalo et al., 2020), bridging the gap between expert tools by scientists and the need of end-users in a co-creation process.

The AIA proposal in Article 3 point 1 defines an 'AI system as 'software that is developed with one or more of the techniques and approaches listed in Annex I and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with'. The AI techniques and approaches listed in Annex I are classified in three groups (Figure 2):

- a) ML approaches, including supervised, unsupervised and reinforcement learning, using a wide variety of methods including Deep Learning (DL).
- b) Logic- and knowledge-based approaches, including knowledge representation, inductive (logic) programming, knowledge bases, inference and deductive engines, (symbolic) reasoning and expert systems.
- c) Statistical approaches, Bayesian estimation, search and optimization methods.

While (a) and (b) groups refer to specific fields within AI in computer science, group (c) includes generic fields that are usually considered outside AI or part of their mathematical or statistical foundation. In the case of statistics, they represent a mathematical science on its own. With the aim of having an open definition of AI system that is future-proof, this classification is neither exhaustive nor exclusive. Some specific techniques and approaches may not be explicitly listed, whereas others can belong to more than one group (e.g. Bayesian ML approaches). Furthermore, according to Article 4 of the AIA proposal, the Commission is empowered to adopt delegated acts to amend this list to update for market and technological developments. Figure 2 illustrates the classification of AI techniques and approaches in the AIA proposal expanded with further subcategories used in this study. Straight arrows show common classification and use of AI techniques, whereas dotted lines show occasional uses of the AI techniques.

Figure 2: Classification of AI techniques and approaches in the AIA proposal expanded with further subcategories used in this study



Source: AZTI.

In the AIA proposal, an AI system is defined as software that is developed with one or more of the techniques and approaches in Annex I of the AIA proposal. An AI system can, 'for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with'. The AIA proposal is quite open; whereby, almost any algorithm can be somehow considered as an AI system if it influences the environments it interacts with. Only the last part of the definition restricts it by requiring that there is an 'interaction'. An interpretation is that an AI system needs to interact directly with an environment (e.g., automatic engine swich off), but it is unclear if it includes systems that only give advice to an operator (who decides to press the swich or not). Such a definition is the result of providing a technology-neutral definition of AI systems that is future-proof (COM(2021) 205 final).

3.1. ML approaches, including supervised, unsupervised and reinforcement learning, using a wide variety of methods including DL

ML can be defined as a set of algorithms that learn from data without predetermined equations or explicit instructions, allowing automated detection, classification, and predictions (Figure 2). The dataset used to build the model is called a training set, where examples are usually labelled by humans. An example is the labelling of fish images with their corresponding species name. The ML algorithms infer the relationships of the labels (class or response variable) among the rest of the data, which are often called attributes, characteristics, variables, or predictors (Table 2). The aim of ML is that the algorithm can predict the label given to the attributes (supervised methods) for each example, data instance or observation. However, sometimes there are no pre-assigned labels, and the ML algorithms learn patterns from the attributes, for example grouping similar data (clustering; Sonnewald et al., 2020) or inferring relationships between attributes (unsupervised learning; Trifonova et al., 2015). Semi-supervised ML algorithms use both, labelled an unlabelled data, for example when labelled data is costly of difficult to obtain.

Table 2: Similarities, differences and keywords associated to specific ML methods

	Labelled	Unlabelled	Optimisation Objective	Keywords
Supervised	YES	NO	NO	Learning from examples
Unsupervised	NO	YES	NO	Learning of patterns
Semi-supervised	YES	YES	NO	Examples & patterns
Deep learning	YES	YES	NO	Convolutional neural network
Reinforcement learning	YES	YES	YES	Agents

Source: AZTI.

Table 2 explains the similarities, differences and keywords associated to specific methods. Labelled and unlabelled refers to the need of an expert previously labelling the data (e.g. species name or type of vessel activity). The Optimisation Objective column highlights if the algorithm aims to maximize or minimize one or more objectives by optimization approaches. This table does not aim to be exhaustive, it is only shown to enable non-experts to easily understand similarities and differences among methods through some concepts and keywords.

DL approaches are a type of ML method usually applied to supervised problems, where large amounts of labelled data are available to apply algorithms based on convolutional neural networks (Malde et al., 2019; Goodwin et al., 2022). Convolutional neural networks are a type of neural network that have proven to be effective in some problems such as image analysis. Neural networks algorithms consist of multiple and flexible parameter layers to learn from data similarly to the way a brain works and is commonly used in ML. Neural networks have been shown to possess high capacity in image recognition or with large amounts of data.

Reinforcement learning is an algorithm that can act or decide (agent) and learn through trial and error towards maximizing a reward or objective. Reinforcement learning is sometimes used for parameter learning in neural networks. Many ML algorithms have the distinction between learning the structure (relationships between variables) and the parameters (weights of these relationships). However, many algorithms impose limitations to the structure and parameters to reduce complexity and avoid overfitting the data. Overfitting is produced in models that are too complex, which fit the training data well but have poor generalization power when new data are available. The overfitting can undermine the trust of ML users if the algorithms do not use robust statistical and ground truth validation approaches (Fernandes et al., 2010; Lekunberri et al., 2021).

In fisheries science, the most widely known and used ML approach is supervised learning. Supervised learning based on data classification from image analysis has often been used for increasing the biological and ecological knowledge required in fisheries management. Supervised learning based on data from otolith image analysis has been applied to infer fish aging with image analysis and ML (Fablet & Le Josse; 2005; Bermejo et al., 2007; Smoliński et al., 2020; Stock et al., 2021) and with DL approaches (Moen et al., 2018; Politikos et al., 2021). Similar approaches have been used for estimating food availability by analysing plankton samples (Zarauz et al., 2009; Irigoien et al., 2009), habitat mapping (Beijbom et al., 2012), invertebrate classification (Kiranyaz et al., 2011; Joutsijoki et al., 2011), and marine litter identification (Cózar et al., 2014; Lorenzo-Navarro et al., 2018; Granado et al., 2019; Kylili et al., 2020).

In relation to fisheries management, ML has been used to estimate stock life-history parameters (Liu et al., 2020; Morais & Bellwood, 2018) and to simulate fisheries management scenarios (Dreyfus-Leon & Kleiber, 2001; Russo et al., 2014). Supervised ML has been used to infer complex stock-recruitment (adults/new fishes), and relationships considering environmental effects (Chen and Ware, 1999; Chen et al., 2000; Huse, G., & Ottersen, 2003; Megrey et al., 2005; Fernandes et al., 2010; Fernandes et al., 2013; Fernandes et al., 2015; Smoliński, 2019). These relationships are key to understanding some of the drivers of fish stocks collapses beyond fishing and to establish fishing rules that allow exploitation while reducing the likelihood of collapse under negative environmental conditions.

Acoustical oceanography consists of emitting sound pulses into the water and analysing their echoes to obtain information (identification, abundance, and size) about the targets present (Simmonds and MacLennan, 2005). Using sonars and echosounders it is possible to observe organisms in the marine environment to depths of hundreds of meters. The new generation of broadband acoustic equipment has increased dramatically the information obtained in each ping, by changing from the discrete, single point response of the 'narrowband' signal (Korneliussen et al., 2016) to the continuous acoustic signature of the 'broadband' one (Stanton et al., 2010; Forland et al., 2014). ML approaches are also commonly used to estimate biomasses and species composition in scientific acoustic surveys through supervised learning (Robotham et al., 2010; Baidai et al., 2020; Mannocci et al., 2021), DL (Rezvanifar et al., 2019; Sarr et al., 2020), unsupervised learning (Korneliussen et al., 2009; Peña, 2018), semi-supervised learning (Woillez et al., 2012) or statistical approaches (Anderson et al., 2007; Boluki et al., 2017). However, early attempts that used more statistical approaches can be found in the literature (Scalbrin et al., 1996; LeFeubre et al., 2000; Lawson et al., 2001). Despite these scientific surveys being key for high quality data, there are important limitations to the amount of data that can be gathered by scientists given the high economic cost of oceanographic surveys. Recently, the complementarity of using data from industry together with scientific data is emerging (Uranga et al., 2019).

There were earlier successful applications of classic ML approaches and image analysis approaches to catches for species identification (Strachan et al., 1990; Storbeck & Daan, 2001; White et al., 2006). These have continued with a recent trend to increase EM (Wang et al., 2018) and capitalizing on neural networks and image analysis methodological development. The utilization of DL has also increased recently on species identification of catches (French et al., 2020; Tseng & Kuo, 2020; Yu et al., 2020; Lekunberri et al., 2021; Qiao et al., 2021; Palmer et al., 2022). However, most of these publications are just proof-of-concept in controlled environments. Recently Lekunberri et al. (2022) have approached the problem of identifying tuna species in vessels using current commercial digitalisation systems already installed on board. Species identification is becoming crucial for catch tracking and monitoring. It is likely that species identification on board vessels will allow quotas to be monitored by industry and authorities in near real time (e.g., daily captures) with standards currently under development. It is also expected that AI will allow the early identification of species that can raise issues with discards.

However, DL requires large amounts of labelled data that are currently difficult to obtain in experimental trials. Some recent research work has focused on fish size estimation without differentiating species (Monkman et al., 2019; Álvarez-Ellacuría et al., 2020; Yu et al., 2020; Garcia et al., 2020). Species identification has been also the objective behind using genomic datasets and ML algorithms (Sylvester et al., 2018; Brophy et al., 2020). Fish species identification and counting with underwater in situ devices has used classification with supervised ML and DL which can be used in biodiversity studies or to improve fishing selectivity (Salman et al., 2016; Marini et al., 2018; Villion et al., 2018; Labao & Naval, 2019). Supervised classification has also been used on genetic data in other species for ecological quality status assessment (Cordier et al., 2017) despite current limitations with genetic data (Hanse et al., 2018). DL as also been employed for underwater detection of sea life and debris floating on the ocean surface using satellite data (Watanabe et al., 2019).

The estimation of presence and intensity of fishing using detailed tracking data from logbooks and VMS is an area where large datasets and ML are evolving. Logbook and VMS data are usually requested by national governmental authorities or RFMOs for monitoring, control, and surveillance systems. Commonly, VMS is a mandatory system for vessels above a given size, but the regulations vary by jurisdiction. Detailed VMS data, however, are usually not shared publicly by authorities or are only provided as aggregated values and with a time lag (Taconet et al., 2019). Alternatively, satellite AIS reporting position through a satellite system are mandatory in all passenger ships irrespective of size, in all vessels >300 MT (gross) transiting international routes, and in any cargo ship > 500 MT transiting within national waters (Eguíluz et al., 2016). AIS was initially intended to improve ship safety by broadcasting and receiving AIS signals to prevent collisions between vessels, and is used by large, oceanic vessels. While the purpose of these signals is to alert nearby marine traffic of a vessel's presence, the messages can be received by a wide array of satellites and terrestrial receivers that operate worldwide (Taconet et al., 2019). ML has been used to analyse VMS and AIS data to differentiate active fishing events (e.g., setting a net) from fish searching activities (de Souza et al., 2016), and to distinguish the fishing gear type (Russo et al., 2011; Russo et al., 2016; Kroodsma et al., 2018; Fernandes et al., 2019; Joo et al., 2021). This differentiation is has enabled the estimation of consequent impacts such as emissions (Coello et al., 2015; McKuin et al., 2021) or seafloor potential impacts (Kroodsma et al., 2018) despite the controversy caused by the data resolution used (Amoroso et al., 2018); or to help in spatial planning (Watson et al., 2018; Queiroz et al., 2019; White et al., 2020) althought there are also some disagreements with the interpretation of the results (Murua et al., 2021a); or spotting illegal fishing (Belhabib et al. 2020; Chuaysi & Kiattisin, 2020; Seto et al. 2020); and forced labour at sea despite doubts raised about its accuracy at local scales (McDonald et al. 2021a; Swartz et al., 2021; McDonald et al., 2021b). However, false positives can have political, economic, and ethical implications (Swartz et al., 2021; Harry and Braccini, 2021). ML has also been used to analyse other various research topics in fisheries sciences (Syed and Weber, 2018; Syed et al, 2018).

Spatial planning is an emerging area where ML is being used to develop expert systems (Coccoli et al., 2018). Moreover, ML is also being employed to generate useful information needed for these expert systems and other approaches. Recently in the Mission Atlantic H2020 Project[81] the current status of mapping human activities and potential role of ML in this mapping as well as the inference of human pressures due to different sectorial activities has been revised. Some examples include: litter estimation from fishing activity (Kuczenski et al., 2021), underwater noise worldwide based on vessel type and their speed inferred from AIS data (Jalkanen et al., 2021), estimation of shipping emission (Moldanová et al., 2018 and 2021, Ytreberg et al., 2021) or oil spill detection and mapping (Pais et al., 2013; Ozigis et al., 2018; Al-Ruzouq et al., 2020).

[81] https://missionatlantic.eu/

3.2. Logic- and knowledge-based approaches, including knowledge representation, inductive (logic) programming, knowledge bases, inference, and deductive engines, (symbolic) reasoning and expert systems

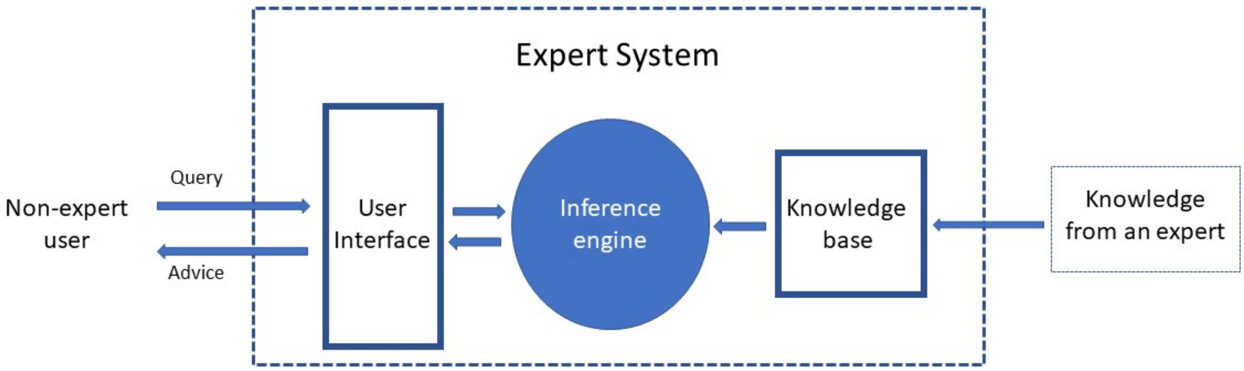
Knowledge-based systems are a form of AI that, instead of learning from data, aim to capture the knowledge of human experts to support decision-making and problem solving. To do so, they usually have two main components: a knowledge base, where the expert knowledge is stored, and an inference engine, which applies reasoning to bring the light new facts and relations between data (Ahmed et al., 2019).

Knowledge bases store information about the real world represented in a way so that a computer can understand and apply reasoning to it. The information in the knowledge bases is described in a logically consistent way, which make them a good tool to easily share expert knowledge. Several knowledge representation methods can be used to formalize the knowledge and make it understandable for computers. One of the most common ways to represent knowledge is the use of rules. These are 'if-then' constructs that allow to express complex statements, such as 'IF you are thirsty THEN drink'. Fuzzy rules can also be used to represent knowledge. These are rules whose antecedents, consequences or both, are fuzzy rather than crisp (Dubois and Prade, 1996), and which are often used by humans on their decision-making in their everyday life. An example of this type of rule is 'IF temperature is hot THEN fan speed is fast', where hot and fast are fuzzy concepts since they do not have strict boundaries. Ontologies are also a well-known way to represent knowledge. They are defined as 'a formal explicit specification of a shared conceptualization of a domain of interest' (Grimm et al., 2007). They define concepts, relations between these concepts and instances to describe the knowledge of a domain of interest, making it intuitively understandable for humans. In 2002, FAO designed the Fish Ontology Service project to create, integrate and use ontologies for information integration and semantic interoperability in fishery information systems (Gangemi et al., 2004). Following this work, they created a network of ontologies to represent information related to fish stocks, formalizing, and integrating data from different sources (Caracciolo et al., 2012). Ontologies have also been used to collect controlled and structured vocabulary of terms that describe fish anatomy, morphology, ecology, and various developmental stages, which can be utilized to classify unknown fish (Ali et al., 2017). They have also been applied to help making early diagnosis of shrimp and fish diseases in aquaculture by considering their morphological symptoms (Tran et al., 2020). Recently, an ontology for assessing fish welfare in aquaculture has been presented, which is applicable to different species, different aquaculture systems and different locations (Tschirren et al., 2021).

Description logics are a family of knowledge representation languages that can be used to represent the knowledge of an application domain in a structured and formal way (Baader et al., 2005). Description logic-based knowledge bases have been built to represent knowledge on coastal ecosystems, population dynamics, descriptions of habitats, interactions between species, etc. This kind of knowledge could help for example in the process of designing management models for artisanal fisheries (García-Allut et al., 2003). Once the knowledge base is built, the inference engine (the second main component of the knowledge-based systems) applies reasoning to extract new conclusions from the knowledge. In this context, reasoning refers to first-order or higher order logic, which can be deductive or inductive. The reasoning is deductive when a conclusion is established by means of premises that are assumed to be true. For example, if it is known that all whales are mammal and all mammals have kidneys, if can be concluded, using deductive reasoning, that whales have kidneys. On the other hand, inductive reasoning tries to induce a hypothesis that generalizes observations. For example, if it is known that tuna is a fish and it lives underwater, and cod is a fish and it lives underwater, using inductive reasoning, it could be concluded that fish live underwater. Inductive logic programming is defined as the intersection between logic programming and inductive learning. It uses logic programming to represent examples and background knowledge, to then derive hypotheses that generalize these examples, learning new relations between data (Muggleton and De Raedt, 1994).

Expert systems are knowledge-based systems (Figure 3) that in an interactive setting ask a person for information and draw conclusions based upon the response, or give advice, emulating the decision-making ability of a human expert. They are useful when an expert is not available to make decisions, when the knowledge of more than one expert is necessary, and when intelligent assistance or training are needed for problem solving. Additional advantages are the educational benefits and the ease of knowledge documentation (Akerkar and Sajja, 2009). Expert systems can be classified into several categories, depending on the knowledge representation they use. Rule-based expert systems are the most common ones, where the knowledge is represented by rules and the inference engine uses deductive reasoning to make decisions or extract conclusions. Fuzzy expert systems, on the other hand, use fuzzy rules to represent the knowledge. Traditional rule-based expert systems have been applied to several problems related to the fisheries sector, mainly in data limited situations. They have been employed in areas related to fisheries management to estimate the vulnerability of some fishes to fishing methods (Cheung et al., 2005). The use of expert systems in aquaculture has also been studied, for tasks such as aquaculture management (Alagappan and Mariappan, 2015) or fish disease diagnosis (Li et al., 2002).

Figure 3: Simplified diagram of an expert system



Source: Reproduced from Tan et al. (2016).

In addition to those traditional expert systems, where a **rule-based knowledge** base and an **inference engine** are the main components, many current expert systems use **ML methods for decision-making**. The main advantage that these systems offer is that they learn from available data instead of learning from formalized expert knowledge, making the process of incorporating new knowledge much easier, or combine both approaches (e.g., Bayesian network approaches). These expert systems can be based on many ML methods, such as artificial neural networks (ANN), Support Vector Machines, Bayesian models or DL methods. In ANN expert systems, for example, the knowledge is encoded within the nodes and the weights of the network, and the network itself generates the inference rules. There are studies that suggest that expert systems can be beneficial for traditional small-scale fisheries (Deepananda et al., 2016), since they allow the knowledge that traditional fishers acquire through their professional life to be formalised for application to the management of these fisheries. Such systems have also been applied to the taxonomic identification of fishes, which is a time-consuming task for non-experts (Chen et al., 2005; Guisande et al., 2010), algae identification (Setiawan et al, 2021) or evaluation of sustainability policies (Cisneros-Montemayor et al., 2018) among other applications. Usually, morphological characteristics of the fishes are analysed to identify its species, but the automatization of this process is a difficult task. Expert systems have been used to make the process easier for the non-experts. Lately, with the growth of available data, ML based expert systems have become more popular, and many applications of these systems to the fisheries sector can be found. Some examples of these applications are the assessment of fish vulnerability to climate change (Chen et al., 2020), early warning systems (Campbell et al., 2013; Granado et al., 2019; Fernandes-Salvador et al., 2021), FROODS (Granado et al., 2021), automatic fish recognition (Sharmin et al., 2019) and Marine Spatial Planning (Coccoli et al., 2018).

3.3. Statistical approaches, Bayesian estimation, search and optimization methods

Even though statistical approaches, Bayesian estimation, and search and optimization methods not being necessarily AI approaches, the AIA proposal includes them within the techniques and approaches that could be used as part of AI systems. The interplay between these concepts is not always clear, but it has been acknowledged that they play a substantial role for the theoretical and practical understanding of AI and its further development (Friedrich et al., 2021).

Statistics is the science of collecting, analysing, presenting, and interpreting data. It has two main types of methods: descriptive statistics that summarise data from a sample, and inferential statistics that draw conclusions about the population from a sample subject to random variation (Casella and Berger, 2002). The later includes problems of point estimation, hypothesis testing, interval estimation, sampling design, model checking and model prediction, aligned with the AI system definition.

Statistics is one of the basic disciplines in fisheries science, where these methods have been used extensively since their foundation (see for instance Ricker, 1945). Examples of applications include models of biological processes, such as length-weight models (Ma et al., 2017; Froese, 2006), growth models (Weisberg et al., 2010; Katsanevakis and Maravelias, 2008), length at maturity relationships (Chen and Paloheimo, 1994; Schnute and Richards, 1990) or stock-recruitment relationships (Subbey et al., 2014; Needle, 2002; Megrey et al., 2005). From an ecological perspective, statistical models have been used to understand how environmental drivers affect fish dynamics (Pepin, 2015), describe essential fish habitat (Guisan and Zimmermann, 2000; Melo-Merino et al., 2020; Pickens et al., 2021) and have been applied to disentangle spatial dynamics (Petitgas et al., 2014), with an increasing interest in recent years in the impact of ocean warming and climate change (Rijnsdorp et al., 2009; Chust et al., 2019; Bruge et al., 2016).

The design of laboratory experiments and sampling for data collection from the fishery or from research surveys often relies on statistical analyses (Thomas et al, 2010; Petitgas, 2001; Hirzel and Guisan, 2002; Borges et al., 2011). The subsequent analyses of these data usually require complex statistical approaches. Some of the most common applications in the case of fishery data are related to characterization of fishing fleets (Dolder et al., 2020), catch and effort standardization (Maunder and Punt, 2004) or comparison of fishing technologies (Miller, 2013); whereas, for fisheries independent data they are related to obtaining abundance indices (Borchers et al., 1997) or characterizing the ecosystem (Doray et al., 2018; Boyra et al., 2018).

Finally, statistical models have been broadly used in fisheries for stock assessment (Maunder and Punt, 2013), stock management (Little et al., 2016) and ecosystem approach to fisheries management (Christensen and Walters, 2004). Statistical developments have been successively introduced into fisheries science as they were developed. One example of how increasingly complex statistical methodology has been gradually introduced in fisheries science are stock assessment models (Maunder and Punt, 2013 and references therein; Buckland et al., 2004; Nielsen and Berg, 2014, Thorson et al., 2015; Anderson et al., 2017). Inversely, fisheries science has also triggered the development of new statistical techniques and approaches. A clear example is the Automatic Differentiation Model Builder (ADMB) developed by Fournier in the late 1980's that was originally designed for fish stock assessment models (Fournier et al., 2010), but has later been applied to many other fields.

Bayesian statistics is one of the two main paradigms in statistics. In contrast to frequentist or classic statistics where the unknowns are considered fixed values, in Bayesian statistics the unknowns are treated as random variables and their distribution conditioned on the observed data is calculated according to the Bayes' theorem (Gelman et al., 2013). It was in the early 1990s when the development of powerful computers and the implementation of computer-intensive methods led to an expansion of Bayesian statistics. In fisheries science, the first applications date from the mid 1990's and were mostly related to stock assessment (Hilborn et al., 1994; Hoenig et al., 1994; McAllister et al., 1994; Punt and Hilborn, 1997). Current applications in fisheries science have a broader scope. Some examples include basic biological processes (Froese et al., 2014), acoustic surveys (Fassler et al., 2009; Juntunen et al., 2012), mark-recapture models (Mäntyniemi and Romakkaniemi, 2002), catch estimates (Fernandez et al., 2002; Hirst et al., 2004), hierarchical spatio-temporal models (Paradinas et al., 2015; Thorson et al., 2019) and relationships with the environment using BNs (Trifonova et al., 2015; Uusitalo et al., 2018).

Search and optimization methods (Hoos and Stützle, 2004; Gendreau and Potvin, 2010; Martí et al., 2018) are methods that select the best solution or best available solution (maximize or minimize one or more objectives or value functions) given a defined domain (or inputs). In simple problems it works by systematically testing inputs and checking if the solution produces a maximum given a value function. In most real-world complex problems optimization methods search for the solutions in a space instead and systematically test all possibilities. There are many different types of optimization and search algorithms, but nature inspired ones are the most used in AI (Granado et al., 2020). Nature inspired algorithms are heuristic methods based on mimicking natural processes. The most used method is the genetic algorithm, which is a population-based approach that iteratively improves the set of best solutions or population by using mutation, crossover, and selection operators (Ueno et al., 2003; Muttil et al., 2005; Álvarez-Diaz et al., 2006; Mesquita et al., 2017). Other examples include (i) simulated annealing algorithm, mimicking the annealing process of metallurgy, which is a heat treatment that involves warming a material and then slowly cooling it (Cook et al., 2005; Vázquez et al., 2016); (ii) ant colony algorithm, which is a probabilistic technique inspired by ant foraging behaviour (Lazarowska, 2014); and (iii) particle swarm optimization, which is a population-based method mimicking the social behaviour of organisms in groups, such as birds or fish (Zheng et al., 2019). Some of the uses identified above are applied to: vessel route optimization (Groba et al., 2015; 2018; 2020; Granado et al., 2021); stock assessments (Maunder et al., 2013); or species distribution models (Pennino et al., 2014).

3.4. Example of fuel consumption reduction

Fuel consumption can represent up to 50% of a fishing vessel's operational costs and is an important contributor to the increment in shipping Green House Gas Emissions and contaminants (Olmer et al., 2017). For instance, global fishing fuel consumption and consequent emissions per landed tonne of catches increased by up to 20% between 1991 and 2011 (Parker et al., 2018). This was due to an increase in fishing effort worldwide without a parallel increase in fish landings (Bell et al., 2017). Furthermore, Lotze et al. (2018) forecast that by the end of the century there will be no increase in global fish biomass in the best-case climate scenario, or up to a 30% decrease in fish catches, in the worst-case scenario; and even worse scenarios are predicted by the next generation of climate projections (Tittensor et al., 2021). This, along with volatile fuel prices, can have a major impact on the fishing industry, fish prices and food security of some countries (Parker et al., 2018).

This is a field of work where different AI techniques can lead to the development and application of effective route and fishing decision support systems to mitigate and adapt to climate change and economic challenges (Granado et al., 2021). This example of a route optimization expert system for fishing vessels can correspond with the combination of the three types of AI methods found in Annex I of the AIA proposal and reviewed in this chapter. A Fishing Route Optimization Decision Support System (FROODS) is an expert system compiling and representing the knowledge from the fishers and managers, taking the decision (type b) but using mathematical optimization and searching methods (type c), and likely to be complemented by ML methods to forecast the best fishing grounds (type b). FROODS may be one of the most complex examples. Most of the examples specified above are simpler and focus on ML (type a) approaches based on learning from data. Nowadays, type b approaches based on knowledge extraction or rules determination are still sparse as a standalone approach in fisheries but are often combined with type a and b methods. Type c methods are often utilized for specific applications such as Bayesian statistics for stock assessments, but not necessarily for its automatic application and not always can be considered AI.

3.5. Opportunities and obstacles consultation with stakeholders

During this study, scientists and stakeholders were interviewed to identify the main advantages, disadvantages, and barriers to the use of AI in fisheries, and the necessary legal framework for its development while preserving people's rights and safety. An online survey was conducted from mid-January to mid-February, targeting a variety of fisheries stakeholders: scientists, European Commission administration (DG MARE), environmental NGOs, and the fishing sector. Four similar questionnaires were adapted to each stakeholder category.

3.5.1. Results of consultation with scientists and researchers

Some scientists considered that AI is currently more applied to data analysis than to data collection or automated sample evaluation, although there is a strong interest in the latter (e.g., automated aging of fish from otoliths, zooplankton samples classification, acoustic data categorization, etc.). In terms of data analysis, the AI approaches currently employed are very close to classical statistical methods, using certain ML algorithms for species distribution modelling or alternatives to standard clustering methods. A researcher commented that there are ongoing projects to research the potential of underwater AI for improving selectivity and monitor fishing effort. According to respondents, sample analysis (e.g., automated fish identification, aging, and all image-related tasks) is one of the research branches with the greatest optimization potential for AI approaches. Use of these methods in fishing gear or remotely via Remotely Operated Vehicle or ROVs has selectivity improvement potential in fisheries. Another scientist pointed out that stock assessment could be one of the first instances where AI is applied since that application does not rely on collaboration from fishers. Along the same lines, another respondent considered that data inputs collected through AI can greatly contribute to population dynamics models (e.g., faster aging of fish from surveys, plankton ID and development of similar environmental indices). As regards fleet monitoring, AI would increase processing efficiency of

EM data particularly from fleets or gears with large numbers of vessels and where poor observer coverage is in place.

Researchers stressed the need for AI and ML experts who have a fisheries science or computer science background who are then specifically trained for fisheries research. Shortages in technological services such as insufficient cloud storage and computing infrastructure are also pointed out as constraints. Therefore, more funds and infrastructure are required for conducting research on AI in fisheries. Other scientists considered that a collaborative process is required where, first, fishers and scientists establish close collaborations. According to some respondents, fishers tend to be reluctant to accept the installation of new technologies for data collection on board their vessels. Thus, the fishers' cooperation is strictly necessary to improve trust and a sense of shared solution co-ownership. Better collaboration between scientists on database sharing of annotated/labelled data is also regarded as necessary. With respect to the main constraints for the use of AI in fisheries research, respondents agreed that there is a scarcity of adequately trained personnel. Some researchers considered that computer scientists mainly work for the industry as they can obtain higher salaries rather than in fisheries science where salary conditions are less attractive. Fisheries scientists are slowly adapting to the new technologies, but there is generally a lack of training in these specialised activities.

3.5.2. Results of consultation with European Commission experts

European Commission experts in fisheries management provided insights on the potential benefits of AI in fisheries control such as image recognition for catch monitoring as part of EM systems. Vessel position data analysis to characterize movement patterns to forecast future vessels' behaviour could enable more focus on control activities on certain vessels based on a risk classification. In turn, data mining could be used for the Fleet Register to spot capacity changes and determine errors/anomalies. Automatic recognition of species using ML could be applied to determine risk areas for more targeted fisheries inspections. Ad hoc sensors for discard detection is also of potential interest for fisheries control. Treatment and analysis tracking equipment onboard small-scale vessels (i.e., overall length below 12 m) can improve spatial and temporal fishing effort distribution knowledge for these boats. AI would also improve fisheries management ability to verify adequate licensing, and detect infringements of seasonal closures and protected areas, thus contributing to solve marine space use conflicts.

European Commission experts in data collection underlined the potential of AI in image recognition to identify species and sizes on board and at auctions, which would increase the quantity, quality, and diversity of the sampling data and traceability of products. Furthermore, sensors could provide real time data collection. Satellite images could be employed for cross checking fishing and enable faster online catch reporting during fishing operations. AI could also be used for the production of interactive maps. However, there are several constraints on the wider use of AI such as considerations on data sharing, data protection, confidentiality, and alleged interaction between data collection for scientific purposes and for control and enforcement. Technical constraints include power supply on small or/and older vessels, connectivity, and network coverage at sea. Lack of trust by the fishing industry can also create an important obstacle for advancement. Quality assurance is yet another crucial factor. Checking data quality and completion of databases with voids currently requires very laborious human work. This may be an area where AI can provide solutions. There is also the risk of how to use all the data collected and how to deal with wrong data use that can lead to 'false news'.

European Commission experts in market policies commented that AI has potential for market intelligence purposes to better forecast production and consumption. In this latter case, AI could be employed to fill the gaps between the latest official data available and the present time. Eurostat data, for example, generally becomes available after a two-year delay. AI could be used to help anticipate what the data over the two most recent years would most likely be. Nonetheless, the main constraint for AI use in the field of market intelligence is the absence of an EC legal mandate for the administration to provide forecasts (production, consumption, etc.) to external stakeholders. Thus, while the production of accurate forecasts would be relevant for market intelligence, legal mandates are not in force yet. Therefore, there are reputational risks such as institutions making forecasts, which go beyond their reporting obligations based on existing datasets. This would in fact influence market operators whose behaviour is altered by these estimates. Thus, there is a reputational risk due to either being wrong in the forecast or passing over institutional roles. Other constraints mentioned by EC officers were the scarcity in skills and training programs for users and also the opposition by some operators who perceived these innovations as controls and limitations on their activities.

European Commission experts mentioned that the EMFAF can finance onboard equipment for vessels in terms of innovation concerning AI, linked to control and monitoring, data collection and research and innovation. For example, Horizon Europe can finance research projects to develop new technologies and innovations including those for fisheries.

3.5.3. Results of consultation with industry and other stakeholders

Respondents from the fishing sector reported that AI is not currently employed in harvesting activities. AI, however, would be of great use for identification of fishing grounds. Regarding the use of AI to reduce fuel consumption, costs, and emissions, some respondents considered again that the short supply of expertise and lack of technology are limiting factors. In turn, a company providing services to large fishing operators commented that they have different AI algorithms in place for processing EM system footage. For this purpose, algorithms are trained to identify fishing operations, detect when catches are brought on board and classify different species. The development of AI will yield benefits such as costs reduction in EM systems, both in terms of reducing footage and its review time. AI developments would in turn facilitate a wider implementation of EM to improve monitoring, control, and enforcement of fishing vessels, particularly where the presence of observers onboard is not practical (e.g., small-scale vessels). Surveys highlighted the necessity to set a new legal framework (or better our understanding of current frameworks) to have a clear view of where AI can be used and how to handle the issues that can arise from it (e.g., privacy and management of failures). The main constraint is the paucity of specific standards setting AI algorithm validation protocols. It is essential to establish well defined guidelines and clear minimum requirements for AI algorithms.

An NGO representative considered that weak monitoring is a major challenge to understand and characterize the interactions taking place between fishing activities and PETs. In this context, AI has the potential to record and improve data provided for long-term ecosystem-based management plans. One of the main constraints for the implementation of AI is that developing, testing and adapting AI tools to the specificities of a particular fishery requires time and staff trained to deal with and analyse large amounts of data. Thus, cost-efficiency studies are required to establish priorities in the use of AI within a long-term strategy. Another barrier for a wider adoption of AI is the introduction of new requirements in a sector that is already highly regulated.

3.5.4. Other recent stakeholder surveys

In the context of the seafood industry, a survey was conducted by EIT Food amongst processors and manufactures exploring their readiness for AI adoption in their processes (EIT Food, 2021). Respondents agreed that the main limitations for a wider AI adoption were the lack of digital skills and the difficulties to acquire the necessary know-how. Another important issue for SMEs within the food industry was the capacity to recruit and retain staff with digital skills in a context where these professional profiles are highly valued in the labour market. These experts normally prefer to work in larger companies which offer higher salaries. In addition, many food SMEs are in rural and often isolated areas with limited access to leisure activities and other facilities which may be less attractive to younger AI skilled staff. Another issue observed in seafood industry respondents was the little awareness on potential benefits offered by AI tools. Many respondents did not understand the meaning of AI and its potential beneficial impacts in their sector. The survey also found that those SME managers most aware of AI technology were also keener to attempt their implementation in their companies. Many respondents considered that failure to implement AI in their industries may let their companies behind in a competitive market. However, the economic cost of implementing AI is currently high and acts as a barrier for a more intensive use of these technologies. Respondents considered that funding plans at EU and national level would lower the economic barriers for a more intensive adoption of AI.

The University of Cambridge (Centre for the study of Existential Risk) and CGIAR (platform for big data in Agriculture) reported on a survey targeting 72 scientists and researchers in the domains of digital agriculture, big data in agriculture and agricultural supply chains to see how they assessed (a) the expected vulnerabilities of supply chains to risks and (b) the expected receptiveness of supply chain phases to AI system (Tzachor, 2020). This report explained AI systems have the potential to mitigate some of the vulnerabilities across supply chains, and thereby improve the state of global food security. This study results suggested that, for the next decade (2020-2030), AI will be needed the most in highly vulnerable supply chain phases in developing countries, where its integration is estimated to be most restricted. On the contrary, although agricultural supply chains in developed countries were considered less vulnerable, the involved agents were significantly more receptive to AI experimentation and integration.

4. SPECIFIC FISHERIES TOPICS DISCUSSION

KEY FINDINGS

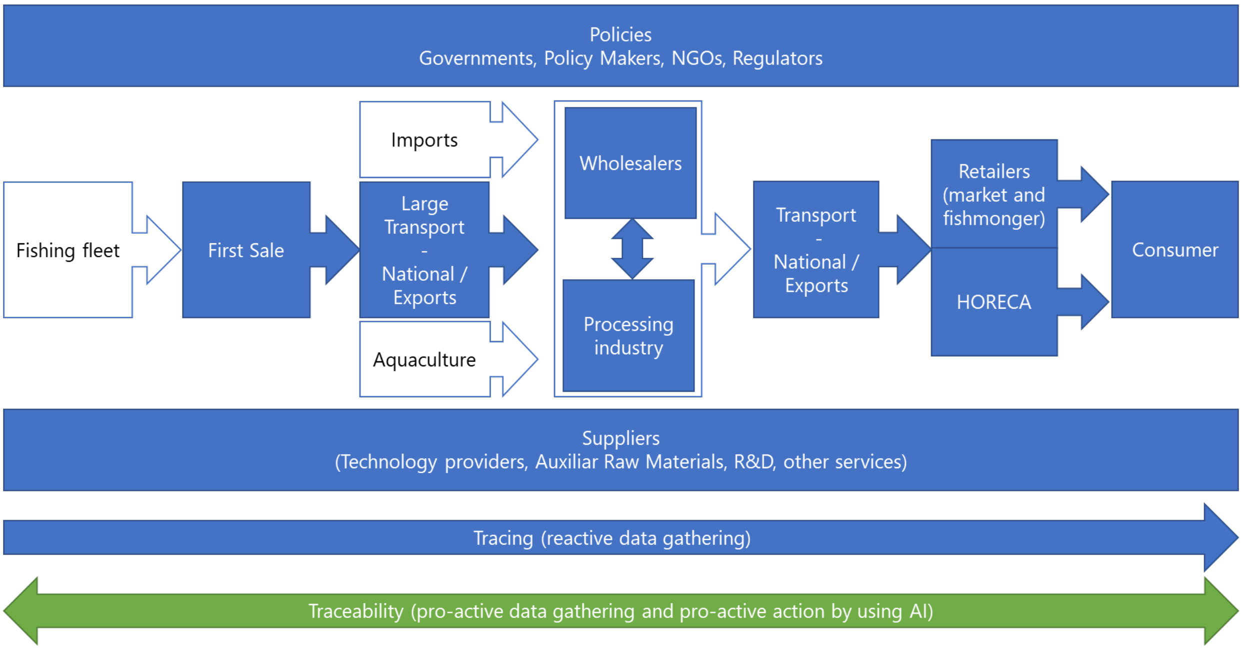
- There is an increasing interest in the application of AI systems in the fish value chain, although current developments are mostly proof-of-concept and not yet commercially operational.
- Traceability and seafood products integrity is where more promising uses of AI application already exist, closer to operational systems within the value chain.
- Lack of data generation and collection, both in quality and quantity, is the main barrier for the application of AI systems in the fish value chain.
- The processing industry is starting to use AI systems to help with the automation of processes in which manual techniques have been traditionally employed.
- AI proofs-of-concept have been developed within logistics for supplier selection, inventory management, storage time prediction, frozen chain break detection, production cost and risk loss estimation and, travel and lead time estimation.
- Machine Learning (ML) has been used to infer consumer behaviour and to forecast economic growth.
- Species selectivity can be further improved with AI.
- AI systems aimed at automated species forecasting and detection, identification and sizing of catches could allow improving fishing decisions and enable quota tracking.
- AI, similarly to digitalisation, is likely to create new skilled jobs while decreasing the need for low skilled ones in the fisheries sector, as observed in other sectors.
- A more digitalised and AI-based fisheries sector might attract new young talent, but it competes against other industries with higher incentives.
- Best practices guidelines for different fisheries sectors are commonly used by management organisations to increase their sustainability and AI systems guidelines can follow this example.
- Existing AI guidelines in other sectors can provide a basis to develop AI guidelines for fisheries following the principles of lawfulness, human rights, responsibility, transparency, sustainability, and wellbeing.
- There are general AI groups and networks at the European level but lacking marine domain knowledge to develop fisheries fit-for-purpose AI systems.
- There is at least one European working group focused on AI for fisheries and several fisheries groups where AI has been discussed, but there is a shortage of sufficient resources.

The EU fisheries sector is large and complex, encompassing an activity which has a relative low contribution to the economy. According to the Scientific, Technical and Economic Committee for Fisheries (STECF's AER, 2021), the fishing fleet generated a gross value added (GVA) of EUR 3.4 billion in 2019. Despite fisheries making a relatively minor contribution to the EU economy, the activity has a high relevance in terms of food security, coastal community identity, employment, and income. The fishing fleet comprises over 57,236 active vessels in the EU, directly employing more than 129,540 fishers. The EU fleets generally operate around the world, including Atlantic Western Waters, North Sea, Artic, Baltic Sea, Mediterranean Sea, Outermost Regions, third country waters and areas under the purview of RFMOs.

4.1. AI use to enhance traceability in seafood product trade across the supply chain

This section focuses on the use of AI to enhance traceability in fish and seafood product trade across all steps of the supply chain. The value chain (Figure 4) describes the full range of activities required to bring a product or service from conception, through the different phases of production (involving a combination of physical transformation and the input of various producer services), and delivery to final consumers: 'from sea to fork' (Rosales et al., 2017). Tracking of information in the fish food supply chain is difficult but needed for consumer trust in compliance with high levels of food safety that European legislation aims to achieve (Nicolae et al., 2017).

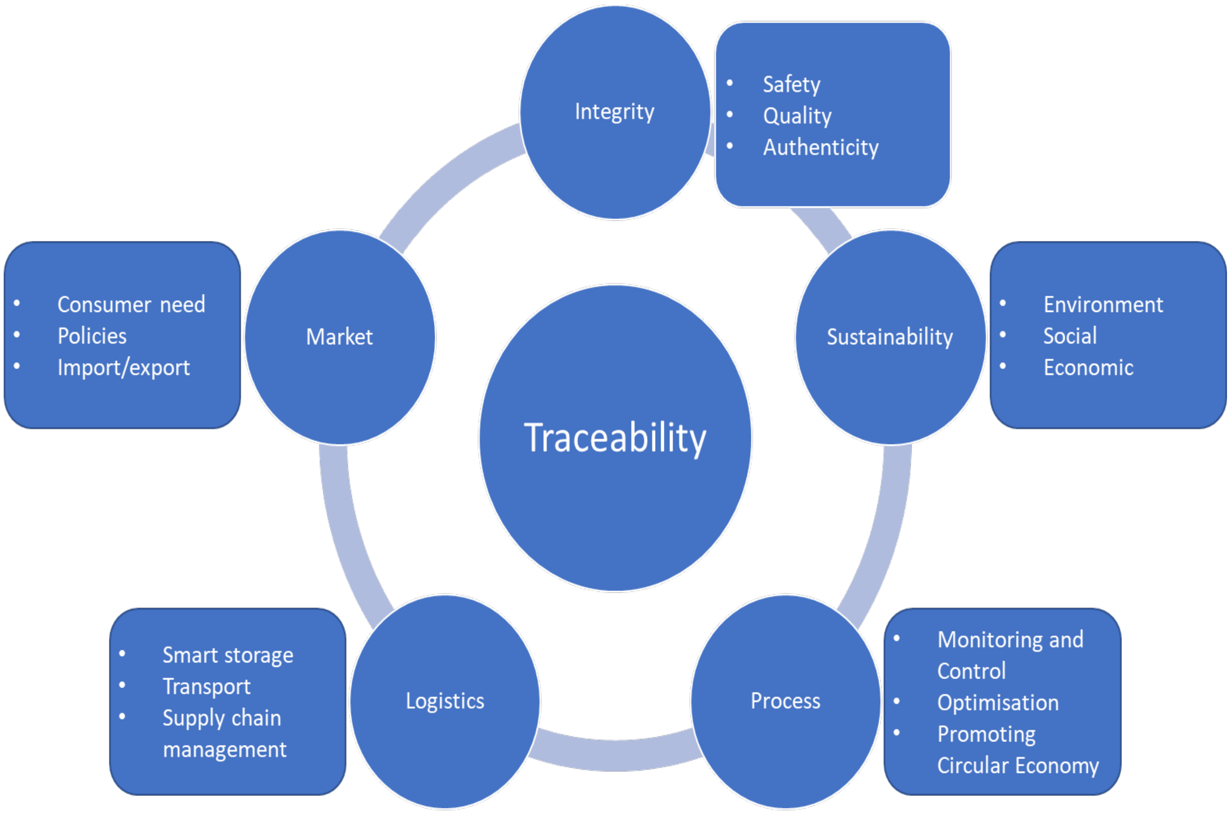
Figure 4: Simplified schema of the Fish Value Chain



Source: AZTI.

Knowledge of the origins of food products is important for public health reasons, and because of increasing people's awareness and demands relating to environmental and social sustainability aspects. Food traceability information must be collected throughout the supply chain and be registered on a platform external to all operators, but available to value chain operators, public health authorities and to customers for making timely decisions about the products with objective information (Oliveira et al., 2021). The basic concept of traceability only includes the record and track of necessary information in all value chain steps from procurement of raw materials and parts to machining, assembly, distribution, and sales. However, advances in the data science allow more key aspects to be included. For example, the use of AI in traceability covers elements like food integrity, sustainability, processing, logistics and market (Figure 5).

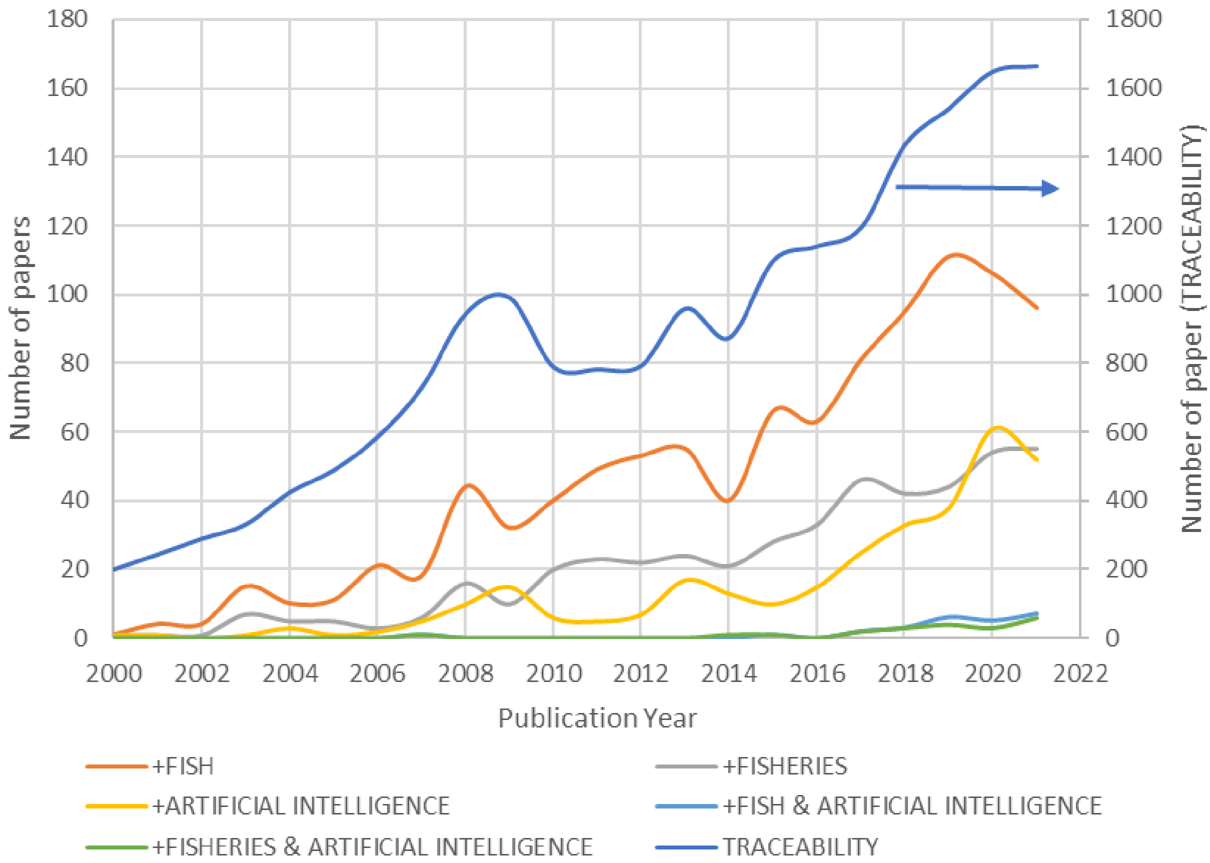
Figure 5: Traceability aspects improvable by AI systems



Source: AZTI.

The implementation of AI in fish chain traceability is driven mainly by regulatory requirements, ICT-Systems, assessment of product quality and improvement of sustainability (Haleem et al., 2019). There is interest in obtaining certifications because they can provide competitive advantages and traceability is a key element. The use of AI impacts traceability in the different steps of the value chain by means of different tools and information that can be managed to improve the overall workflow and the ability to track events with accuracy throughout all the stages. Traceability is a key requirement for trustful AI systems in the supply chain (Mora-Cantallops et al., 2021). The evolution of the papers published in the topic of traceability in combination with fisheries and/or AI keywords show a constant increase (Figure 6). However, only 100 publications out of 1,600 refer to traceability, and this number drops to 6 if the AI keyword is added.

Figure 6: Published papers related to fisheries, AI and traceability keywords



Note: Right axe: traceability; Left Axe: traceability combined with fish, fisheries &/or artificial intelligence.

Source: AZTI

4.1.1. Chain sustainability

The implementation of AI could help to improve the social, environmental, and economic chain sustainability level (Vinuesa et al., 2020). Chapter 3 provides several examples of AI systems helping with sustainability improvement at the beginning of the chain, for example in fisheries tracking, catches monitoring, spotting illegal fishing, spatial planning, reducing fuel consumption and associated emissions. However, different agents along the value chain also demand improvements in sustainability for their processes (Tzachor, 2020).

4.1.2. Seafood products integrity

Food Integrity, fraud misidentification, and adulteration of food, whether intentional or not, are concerns worldwide. The complex organisation of the international fish supply and market chain, makes it difficult to prevent counterfeiting and falsification of these products. Species identification is an essential aspect to expose commercial fraud. However, many species cannot be easily identified visually, and the development of fast and reliable omics strategies and AI has been attracting great interest. Studies on methodologies for fish and seafood **authenticity** by food scientists have increased considerably in recent years (Ghidini et al., 2019; Monteiro, 2021). Wang et al. (2022) presents a literature review on ML applications for monitoring and predicting **food safety** and references several studies addressing fish safety. Also, ML approaches in analysing bioaccumulation of pollutants in fish tissues to effectively estimate tissue concentrations of heavy metals have been developed (Petrea et al., 2020).

4.1.3. Fish processing and circular economy

The **fish processing** industry has traditionally employed manual techniques in most of the steps in the chain, which leads to inefficiencies and fluctuations in the quality of the final product and reductions in economic sustainability. Seafood by-products are significant, constituting approximately 40-60% of the weight (Islam et al., 2021) and they have become an economic burden for fish industries. Cooney et al. (2021) proposed a multi-criteria decision support tool employing ML techniques as a solution for the sustainable production of fish feeds. Also, ML has been used during processing to detect bones in fish products (Mery et al., 2011). Smart machines (Elíasson, 2019) can avoid bone removal and cut fish differently, depending on the quality of the fillets, keeping a good portion of the most expensive parts instead of having to downgrade the whole defective part to a lower-cost product. Image analysis combined with DL have been also used to help in the packaging stage (Xu et al., 2018). In Azadbakht et al. (2017), an ANN was employed to predict the energy and exergy parameters applicable to seafood processing.

In a **circular economy**, AI systems can enable a transition of the production chain toward a low-waste and resource-saving model, thus making companies more resilient (Uribe-Toril et al., 2022). There are three main aspects where ML techniques can be applied (Akinodnd Oloruntoba, 2020): 1) design of Circular Materials by using rapid ML-driven prototyping and testing; 2) operate Circular Business Models with ML improving product circulation through intelligent demand prediction, pricing, inventory management and predictive maintenance; and, 3) optimising Circular Infrastructure through ML-based enhancement of components remanufacturing, products sorting and disassembling and materials recycling (e.g. Pichara et al., 2021).

4.1.4. Logistic aspects

The rapid growth in the volume of data generated in supply chain management systems has forced companies to develop new technologies capable of interpreting large amounts of data in terms of storage, transport, risk assessment and supplier selection. AI methods are especially appropriate for coping with this major data-related challenge (Tirkolaee et al., 2021).

Traceability in the transport sector refers to the ability to follow and monitor container movements and trace back information from its internal and external environment. Stakeholders involved in multi-modal shipment agree on the need to develop tools for the container supply chain risk management that enable prompt actions if required. To achieve quality and safety of seafood during container multi-modal shipment, supply chain management must fulfil four requirements: 1) control the expeditions by enabling the automatic exchange of tracking and monitoring data; 2) generate alerts to warn supply chain actors of abnormal events so that they can take prompt corrective actions; 3) improve decision-making through an analysis of data collected during expeditions; and, 4) perform predictive analysis to detect hazards and to suggest avoidance plans dynamically. ML approaches are widely used to estimate travel and lead time (Dosdoğru et al., 2021; Askin et al., 2017). In Alnahhal et al. (2021), the dynamic weekly forecasting process for each customer order was performed from the point of view of the third-party logistics provider. Furthermore, in Atwani et al. (2020) a neural network was applied to setup times, optimal lot-size across SC processes, and required inventory levels to demand and production planning.

Risk assessment is a crucial step for identifying risks presented by supply chain partners who can have a significant impact on a company's ability to achieve its production targets. ML and big data analytics have also been utilized to deal with risk assessments. Artificial neural networks (ANNs) are among the most used ML techniques that have shown a good potential in accurately modelling risk assessments (Tirkolaee et al., 2021). For example, Bruzzone & Orsoni (2003) employed an ANNs to calculate the expected costs and risks of production losses and compared them with another methodology based on simulation, highlighting the better performance of AI.

Supplier selection is the most important stage of the purchasing activity (Pang et al., 2017). Due to the fundamental role played by suppliers in time, costs, and quality, supply chain managers typically dedicate much of their effort in the supplier selection process. In Zhao and Yu (2011), an ANNs was used to solve the key problems of the Case Based Reasoning system of supplier selection. Thanks to its strong self-adaptability, the ANNs improved the accuracy of updating phases and the efficiency of the decision-making in the companies' process of supplier selection. Bayesian learning was applied in Chen et al. (2009) to evaluate the suppliers' reliability and to show that, although several parameters were not considered, the model remained flexible and can be even further improved by including those other variables.

Storage accounts for significant costs of the supply chain management, averaging 15%-35% of their total business value per year (Tirkolaee et al., 2021). Supply chain inventory management seeks to decrease costs, increase product variety, and improve customer service as well. However, precisely estimating, predicting, and accessing the information by traditional decision rules is hard because the uncertainty associated with this information is usually high according to the experience of inventory managers. In recent years, the inefficiency of traditional methods in facing uncertainty has led researchers to apply AI for better results. For example, ML tools can detect in detail patterns in warehouse datasets. Gumus et al. (2010) applied neural networks to lead-time forecasting, resulting in inventory management performance improvement. In Tan et al. (2020) neural networks were used to predict storage time of glazed frozen squids and Loisel et al. (2021) presented several ML techniques for detecting frozen chain breaks. All the studies cited in that work demonstrate that ML can be applied to estimate the temperature distribution inside a pallet in several stages of the cold chain. However, obtaining high-precision predictions for the temperature distribution in a pallet using a limited number of temperature sensors was a challenge for ML, highlighting the need for high data quality and quantity to feed AI systems.

4.1.5. Market aspects

The fresh fish market has experienced significant changes and new trends are emerging (EU, 2020). This is of particular interest to international researchers for political and economic reasons. Market aspects deal mainly with consumer need/behaviour, policies and product import/export where quality and customer service are valued under the constraints of acceptable costs.

Consumer behaviour is a determining factor for fishery and distributor operations. Consumers make buying decisions based on market conditions and on various attributes of the product such as the species, the place of purchase/catch, the size and quality (Al-Mazrooei et al., 2011). The high amount of data generated by consumers in the form of purchase choices, reviews, ratings, and comments can be exploited by using ML (Shrirame et al., 2020). Passos (2019) carried out an in-depth study on consumer behaviour related to fresh fish. This behaviour was defined through a series of critical variables such as the frequency and value spent, the adherence to promotions, the relative consumption of different species of fish, the type of fish (farmed or wild), and even the relationships among the various products in the shopping cart. The results emphasized not only the clear differences among groups of fresh fish buyers, but also their preferences. In Petrea et al. (2020) three time series algorithms were used to forecast fish consumption. The preferences in association with the socio-economic characteristics of the consumers were considered to assess how they would influence the intention to buy these products in the future. Origin and traceability of fish products were particularly relevant. The analyses of socio-demographic characteristics revealed the emergence of new types of consumer preferences.

Public **policy** plays a major role in realising a sustainable fishery. However, there is a major gap in research on policy interventions that promote AI use for sustainable fishery systems (Ebrahimi et al., 2021). Fish detection and counting are crucial for policy formulation to effectively control fish harvesting and prevent stock depletion (see Chapter 2 of this study). However, only one of the reviewed articles (Fanelli et al., 2020) touches upon policies such as the Blue Growth call, which points at AI as a tool to strengthen the marine industry and support the global monitoring of the marine environment.

Trade factors (**Import/exports**) are important ingredients for the analysis of economic growth. There have been several attempts to link trade factors and economic growth. However, formulating models capable of capturing the effect of import/exports on economic growth is a complex task. Countries with high incomes tend to trade more, even though incomes may not be due to trade. Thus, it is crucial to find more advanced algorithms for the prediction of economic growth rate in relation to trade, imports, and exports. For example, Feng & Zhang (2014) employed an ANN for economic growth forecasting and Sokolov-Mladenović et al. (2016) used another ANN to overcome the problem associated with economic growth forecasting high nonlinearity based on trade.

4.2. The use of AI to develop and use more selective gears and fishing techniques

Fishing selectivity is the ability to target and capture fish by species, size, or sex (or any combination of these) during harvesting operations, allowing all unwanted catch to be released unharmed or not be caught at all. The selection process begins when searching for fish and continues when fish accessible to the gear are caught or not. Then the fish that encounter the gear are either retained or they escape whilst in the water, and the final selection process takes place once the gear has been recovered and brought on deck. There, fishers decide whether the fish should be landed or discarded. Fish discards refer to the portion of a catch of fish which is not retained onboard during fishing operations and is returned to the sea. In EU waters, for example, fisheries activities are quota regulated and subject to the LO (CFP). The LO means a step forward in resource sustainability but imposes a challenge for managers and industry (Catchpole et al., 2017). Different fishing gears and fishing strategies lead to incidental fishing a variety of species of non-target species (bycatch) with complex trade-offs (Oliver et al., 2015; Hazen et al., 2018).

Traditionally, to address different regulation challenges, fishers and scientists have focused on selective fishing gear development, by physical gear modifications to influence the targeting and sorting process. Nowadays EU vessels operating in EU waters are starting to improve their selective performance by adjusting where, when, and how they fish. However, commercial fishing is still today a relative "blind process" where operational decisions are based on catch compositions from the last haul. This implies that fishers obtain too little information too late, resulting in a limited control over the catch process. Additionally, a single fishing operation may represent a four to eight hour process with undetermined fuel consumption, which can have important consequences in time and money invested if there is a poor catch of target species. Fishers lack efficient decision making tools to better control the catch composition that is taken on board. The fishing sector would benefit from improvements in fishing precision (species and sizes selectivity), ecosystem impact mitigation (development of lower impact and efficient gear), fuel consumption and CO2 emission reduction and an increase in regulation compliance. Therefore, a fisher should be able to monitor or even better forecast the following information: 1) the target species fishing ground areas; and 2) the species and sizes being caught.

4.2.1. AI for forecasting and planning activities

The fishing industry is starting to utilize Earth Observation data to characterize environmental conditions of marine areas to geolocate high-quality fishing grounds with less effort (i.e., for minimizing time, fuel, and costs). For example, high digitalisation of purse seiner tuna vessels can help with data availability (McCauley et al., 2016). However, due to the large volume, diversity of sources and quality of recorded data, they are sparsely tapped into for further analysis and remain intact and unstructured, thus requiring lots of resources for real-time analysis. Big data processing techniques, enhanced by ML methods, can increase the value of such unexploited data and their applicability to society, industry, and management challenges. ML has already started to prove its potential in marine sciences applied to fisheries forecasting (Fernandes et al., 2010; 2013; 2015). Other tools such as optimization heuristics, designed in recent years to optimize their routes (Groba et al., 2015; 2018; 2020; Granado et al., 2021) or Species Distribution Models to assist the fishing industry optimizing distribution for catches (Breece et al., 2021; Dolder et al., 2018; Stock et al., 2020), have shown to be promising tools for dynamic ocean management. These tools enable more efficient adaptation to changing biological, oceanographic, or economic conditions and are faster than traditional, static, time-area closures (Breivik et al. 2016; Dunn et al. 2016; Howell et al. 2008, 2015). Despite recent AI fishery-specific developments (e.g., SusTunTech H2020 project[82]), the AI implementation in the fishing industry is behind other shipping sectors, both in state-of-the-art and day to day applications (Christiansen et al., 2004; Agra et al., 2015).

4.2.2. AI for improving timely observation and catch monitoring

In-trawl camera systems are being introduced in several fisheries (Rosen and Holst, 2013; Mallet and Pelletier, 2014; Underwood et al., 2015; Williams et al., 2016; DeCelles et al., 2017). However, these systems have been used for scientific monitoring purposes only without the operational use of AI systems. The developed catch monitoring methods are associated with extensive storage and manual processing of video recordings (Needle et al., 2015). To become an efficient decision support tool, these systems require automated processing of the data. Recently, this automated processing has become more common in various industries, and fisheries are no exception. Several studies describe automated fish detection and classification commonly performed with the aid of DL model application (Allken et al., 2019, 2021; Christensen et al., 2019; French et al., 2020; Garcia et al., 2020; Lekunberri et al., 2021; Sokolova et al., 2021a,b; Tseng and Kuo, 2020).

These studies demonstrate that the DL models for object detection and classification are efficient tools for processing the on-board (French et al., 2020; Khokher et al., 2021) and the underwater collected catch recordings (Christensen et al., 2019; Sokolova et al., 2021a,b). Underwater video recordings are often challenged by poor visibility conditions, especially in demersal trawls, for which technological advances supporting AI development will still be required (Sokolova et al., 2021b). In this area, 3D camera systems employing methods such as stereo imaging (Fisher et al., 2013; Rosen and Holst, 2013) or 'time of flight' (time taken for a light pulse to reach the object and return) developed in the Utofia H2020 project[83], may soon permit fish position and size capture even in turbid environments.

Recent studies have developed algorithms applicable to AI automated data processing that would allow near real-time observation (e.g., H2020 projects SmartFish[84] and DeepVision[85]). Present and

[82] https://www.sustuntech.eu/
[83] https://www.utofia.eu/
[84] http://smartfishh2020.eu/
[85] https://www.deepvision.no/

future work includes embedding these algorithms in portable hardware for practical use and exploring the possibilities for automated catch measurements. Nowadays, these AI tools still require long distance wired communications from the vessel to collect data, which can be difficult to handle, especially in deep sea fisheries, and are more expensive. Therefore, further work should also focus on developing wireless communication systems (e.g., acoustics).

4.2.3. AI for timely operational decision-making

Advances in AI image analysis, with ML and other techniques will allow real-time species identification and automatic analysis of acquired images, permitting the skipper or a control system to make real-time fishing activity decisions. These could be as simple as deciding to continue or stop fishing, based on observations of what type of fish are present in the fishing ground or enter their gear. Alternatively, they could be used in conjunction with remotely controllable selectivity instruments that, for example, in the case of trawl gears, open/close the codend at the end of the net or operate flaps/doors that direct fish into different compartments.

The AI systems could be trained to control other stimuli; for example, to remotely switch lights on/off to attract/repel species (e.g., SmartFish H2020 project[86]), or control pulses and hydrojets (Jordan et al., 2013). AI can also be applied in sail drones that assist fishing fleets. During fishing operations, skippers can detect pelagic fish in the water column by employing the on-board echo sounder of the fishing vessel. However, to date these echo sounders lack the ability to produce information or parameterization of the distribution of fish species present, estimated bycatch and potential discard rates (Christensen et al., 2019). Autonomous vehicles combined with AI methods have the potential to search for biomass, register species and size that would directly inform fishers to substantially improve selectivity. Transforming the current blind/semi-blind fishing process into a more informed process will improve the sustainability of commercial fisheries both in economic and ecological terms. Fishing only when the availability and catch composition is favourable will lead to increased catch efficiency, reduced fuel consumption, and minimized seabed impacts (of those fishing gears interacting with the bottom). Besides, full visualization of the catching process could also highlight fisheries/areas/periods in which selective gear use is most needed and therefore, target the development and optimization of selective fishing gear for hotspot areas and seasons.

As a final consideration, fishing activity is nowadays mainly regulated through technical measures (Regulation (EU) No 2019/1241), which set out rules on how, where, when, which and how many marine biological resources can be caught in EU waters to conserve target species and protect marine ecosystems. However, the performance of a fishing gear depends on the structure of the fished population, the Minimum Conservation Reference Size, the TAC, etc. that can vary inter-annually. Decision-making on technical regulations usually entails a slow and inflexible process. Full near real-time documentation on catches or control on what can be caught by the fishing gear should lead to a more immediate, flexible, and dynamic application of conservation measures and decrease fisher opposition to regulations.

4.3. AI as a driving force for young people to look for jobs in fisheries

This study also examines AI as a driving force for young people to seek jobs in the fisheries sector. Employment in the fisheries sector is a subject close to the heart of the European Parliament. For example, the European Parliament resolution 'Fishers for the Future: attracting a new generation of workers for the fishing industry and generating employment in the coastal communities'

[86] http://smartfishh2020.eu/

(2019/2161(INI) adopted in September 2021. The European Parliament stresses that improving fishers' living standards, with better working and safety conditions, is one of the elements to attract young people and achieve the generational renewal (point 24). The European Parliament also affirms that appropriate and specific education and training are essential to encourage young people to perpetuate coastal fishing activities and traditions (point 47). It encourages the creation of an association of young European fishers to promote the generational renewal of the fisheries sector (point 48) and welcomes the financial support from 2021-2027 EMFAF to support young people (point 97). In addition, the European Parliament underlines that the actions to attract young people to fishing activity must ensure gender balance and consider the role of women in the entire fishing industry (point 61).

Fishing activities are hard due to the often-long periods at sea separated from family and friends, intense physical demands, and safety risks. These conditions make this sector unattractive to younger generations and there is now a high demand for a new specialized workforce. Some of these historical issues are improving due to technological improvements. For example, a growing number of ship-owners are installing computer systems and faster internet connection onboard to guarantee access to internet and social media, so fishers can communicate regularly with family and friends. On the other hand, there are applications focused on fishing efficiency that contribute to reduced time spent at sea (e.g., faster fishing trips). In addition, considering the meteorological conditions among other factors, there are AI-based applications that investigate reducing the energy consumption and time at sea and increase safety (e.g., alert of dangerous weather conditions). These are examples of technological applications, potentially improvable with AI, that could contribute to reduce the hardship of the job and make this sector more attractive to young people interested in technical and computing skills. Moreover, moving towards more autonomous fishing vessels would lead to reorganisation of jobs in the industry, requiring less people working onboard at sea and more in land supporting with technical and AI skills. Displacement of labour from the vessel to the office in the fishing sector can be beneficial from a human safety, health, or well-being perspective (e.g., lower risk of injuries, more time with family). However, establishing inter- and multi-disciplinary research teams is difficult, but it can also help attract talented young people looking to cooperate in a thriving work environment that covers multifaceted aspects (Haapasaari et al., 2012). Modernising fisheries with the introduction of new technologies, such as AI, with their increasing appeal for the younger population, will help make the fishing industry more attractive to the next generations. In recent times, new generations of skippers for example are more accustomed to novel technologies such as high-tech sonars, radars, echo-sounders, oceanographic software, etc. (Lopez et al., 2014). Younger fishers with skills in modern fishing technology are highly valued by fishing companies, especially in modern industrial fleets due to their increasing reliance on these technological aids.

As fishing technology, assisted by AI, continues to advance towards vessels requiring less onboard crew (e.g., fishers) and relies more on assistance by highly skilled land-based staff, this could attract younger generations who are interested in the technological world. The International Maritime Organization (IMO) has analysed the use of maritime autonomous surface ships (MASS) as a key strategy direction to integrate new and advancing technologies in the regulatory framework. The IMO defines autonomy for vessels in four ascending categories, from the first category (ship with automated processes and decision support) to the fourth category (fully autonomous) corresponding to vessels with AI systems. This involves balancing the benefits derived from new technologies against safety and security concerns, the impact on the environment, the potential costs for the industry and their impact on personnel, both on board and ashore. In this regard, the IMO has recently finalized a legislative scoping exercise encompassing an extensive range of issues, such as the human element, safety, security, liability and compensation for damage, interactions with ports, pilotage, responses to incidents and protection of the marine environment. There are other aspects of concern with regards to the use of MASS, including the clarification of the meaning of terms like ‘master’, ‘crew’ or ‘responsible person’ in different degrees of autonomy (remotely controlled ship, fully autonomous ship). The IMO considers that the best way to address the legal issues raised by MASS is by developing a specific legal framework, the ‘MASS Code’, that is expected to be completed in 2025.

Finally, these analyses will help to provide good practice recommendations on the use of AI in fisheries during these key early stages of their emerging application within the fisheries field. Socialization of the best practices among fishing communities, industry and fisheries managers will help raise awareness amongst these key stakeholders as to the benefits of the adequate and fair use of these tools. This can generate acceptance and appreciation of the positive results of AI technology in their daily work. These sets of guidelines will also identify poor AI technology practices which can potentially prevent or deter future AI developers from its misuse and help protect the rights of those involved in fisheries activities. These AI good practices agreed among fisheries participants will form a first blueprint on which future recommendations can be incorporated as the state of this technology and its applications in fisheries inevitably develop over time in the coming years. There is generally still a slow formalized integration of science, regulatory authorities, and the fishing industry. AI tools can help to build trust among fishers, scientists and society through neutral and impartial decision-making processes based on quality data. Results from several recent studies hint at the potential benefits of using AI for social good, specially related to agriculture in developed countries.

4.3.1. Theoretical and empirical evidence in the economy

The digitalisation processes in the economies have shown that while high skilled jobs increased, low skill ones decreased (Balsmeier & Woerter, 2019). Although there could be an initial labour saving, markets have the potential to compensate it through higher levels of productivity that lead to induce lower prices and higher quantity demand which at the end increases the labour demand of firms. AI is not different from the general aspects of digitalisation explained above. However, collaborative AI (when both agents – human and machine- are autonomously contributing to solve a single problem) can make low skilled workers focus on tasks where they have comparative advantages over machines, increasing the individual productivity of workers (Qaiser et al., 2020). Fisheries can be an example where collaborative AI can help in predicting patterns while fishers can take advantage of these automatic predictions to catch their quotas and reduce working time or fuel consumption (Fernandes et al., 2021). This collaborative AI, with modern technologies, which assists in improved fishing yields, can also boost recruitment of young(er) fishers to cover the existing scarcity of labour renewal in the fisheries sector. While women play a prominent role in the fisheries sector around the world[87], their contribution is still overlooked (Harper et al., 2017; Gopal et al., 2020). In a world in which the working lives of women will be affected by AI (Collett et al., 2022), AI could also help to empower women in the fishery sector. Furthermore, this would be critical to avoid gender-biased AI systems (Leavy, 2018).

Examples from aquaculture show a trend of increased AI applications in this sector and has attracted some start-up firms[88]. Expansion of aquaculture can increase through help of novel emerging technologies which have the potential to revolutionize this industry. These technologies include robotics, information/digital technologies, offshore farming, RAS, replacement of fish meal and oils with alternative proteins and fish oil, and oral vaccines. These technologies will also generate opportunities for businesses and jobs, including opportunities for women and younger people. However, some of these new technologies may generate barriers for small/family-based fish farmers,

[87] https://www.europarl.europa.eu/EPRS/TD_Women_in_fisheries.pdf
[88] https://www.aitrends.com/ai-and-business-strategy/ai-applied-to-aquaculture-aims-for-improved-efficiency-healthier-fish/

who lack financial resources to adopt them (Yue, 2021). Although it is still in the 'proof' of concept stage, the Kindai University Aquaculture Research Institute (Shirahama, Wakayama Prefecture), Toyota Tsusho Corporation (Nagoya, Aichi Prefecture) and Microsoft Japan (Minato, Tokyo) have collaborated to develop a new aquaculture selection system to automate the manual process for selecting fingerlings for cultivation. Some evidence in other non-EU Member States show how AI reduces the average age of the aquafarm workers. This is the case in the South Korean aquaculture industry[89]. Valuable skills are not always transmitted to young generations, and in this case, AI can help to collect and reproduce them. For example, the 'tuna scope' app in Japan[90] evaluates the quality of tuna at the selling point.

4.3.2. AI based products in the maritime sector

The offer of AI products for the maritime sector has increased in the last decade as shown in the creation by Lloyds Register (LR) of its Artificial Intelligence Register[91]. This is a standardized digital register of LR-certified AI suppliers and solutions, which is the first of its kind for the maritime industry. The applications range from digital twins, virtual commissioning, and autonomous navigation systems. To support this uptake in technology, LR's AI Register has been developed to signpost proven and reliable AI technology to help maritime stakeholders benefit from the latest applications. Each AI solution introduced in the LR AI Register will be categorised against their LR certification status, such as Digital Twin Ready, Digital Twin Approved, Digital Twin Commissioned and Digital Twin Live from LR's ShipRight Digital Compliance framework. The AI Register will also provide details about what each specific solution offers, such as key business benefits, target applications, functions, and performance. The AI providers currently listed in LR's AI Register include international firms such as Furuno, HAT Analytics, Korea Shipbuilding & Offshore Engineering (KSOE), Samsung Heavy Industries (SHI), Hyundai Heavy Industries (HHI) and ZhenDui Industrial Artificial Intelligence (ZDIAI). At present, virtually all AI solutions proposed by these companies are digital twins dedicated to ship failure prediction and anomaly detection, only one of the products in this register is dedicated to route optimization.

Outside of standardized services, there is a growing number of companies dedicated to offering AI-based solutions to companies in the maritime sector, but most of them focus on two problems, the prediction of ship arrivals, which is important for the management of commercial ports, or the calculation of optimal routes between ports to minimize time or fuel consumption and weather associated risks. Most of the companies offering these AI products are small start-ups or spinoffs of bigger companies, this being one of the typical characteristics of an emerging market.

4.3.3. AI based products in fisheries and fisheries science

The search for similar AI solutions used specifically in the fisheries sector gave almost no results when searching for industrial products developed for fishers, only some vague claims of AI-based bird detection by two radar manufacturers. In comparison, the number of AI solutions being used in fisheries monitoring and fisheries studies by the scientific community is quickly increasing as shown in Chapter 3. The bibliographic review by Honarmand Ebrahimi et al. (2021) shows that interest in using AI tools for fisheries research has increased drastically, as exemplified by the eight-fold increase in fisheries AI papers published between 2011 and 2020. When Beyan and Browman (2020) asked for contributions for a special themed issue by the ICES Journal of Marine Science the main topics forwarded were:

89 https://www.ajudaily.com/view/20201216100927147
90 https://www.theverge.com/21318402/japanese-app-ai-grade-fish-quality-tuna-scope-sushi
91 https://www.lr.org/en/ai-register/ai-solutions/

- Automatic marine ecosystem monitoring based on visual and/or acoustic data.
- Automatic fish detection.
- Automatic coral reef state detection (e.g., health, dead/alive).
- Underwater measurement of fish length.
- Automatic fish counting, for example to analyse the effect of global warming.
- Automatic fish tracking (e.g., swimming speeds and trajectories).
- Automatic fish species classification/recognition/identification.
- Characterizing interactions between fish (e.g., predator–prey relationships).
- Fine-grained automatic object recognition in underwater visual data (e.g., substrate classification, plankton).
- Applications of block chain technology/systems.
- Automatic detection/classification of acoustics produced by marine animals (e.g., whales, dolphins, and fish).
- Automatic systems for fisheries management.

These research topics fit very well into the research agenda proposed by Ebrahimi et al. (2021). Both Honarmand Ebrahimi et al. (2021) and Fosso Wamba et al. (2020) found that academic interest in AI-inspired fishery literature focuses mostly on automation of fishery resources monitoring, while up till now, key issues in AI development for fishers' needs and policy responses by governments have received limited attention.

4.4. Best practices of the use of AI in the fisheries sector in the EU or worldwide

In this section good practices in fisheries are introduced and good practices for AI are revised to understand their applicability to fisheries.

4.4.1. Fisheries good practices

Fishing practices develop through a combination of social, economic, environmental, and regulatory factors operating in each fishery. To achieve sustainable fisheries outcomes local, national, and international management bodies like RFMOs adopt conservation measures that set out to protect stocks from overexploitation and mitigate ecosystem impacts, while achieving Maximum Sustainable Yields (Gilman et al., 2011; 2014). Numerous institutional measures establish best practices on aspects such as stock exploitation limits, vulnerable species bycatch release methods, marine pollution prevention or aquaculture standards. One of the better-known best practice guidelines is FAO's Code of Conduct for Responsible Fisheries (FAO, 1995), on which many regional and international fishing regulation principles are based. These user guidelines were defined mostly in a top-down fashion by fisheries management bodies, in which operational requirements were defined with little consultation with the fishing industry. This non-inclusive approach has led in some instances to poor application and compliance of regulations by fishers who feel excluded from decision-making processes (Kirby and Ward, 2014; Barz et al., 2020).

In recent years, the role of fishing industry in the development of better practices has been instrumental thanks to joint collaborative efforts with other stakeholders like scientists and NGOs (Poisson et al, 2016; Österblom et al., 2017; Koehler, 2020; Murua et al, 2021b;). This proactive role of the fishing industry has been partly instigated by growing consumer and market pressures to deliver sustainable seafood (i.e., eco-certified products) (Adolf et al., 2016). For instance, the Global Seafood Alliance has set best practices in aquaculture industry standards covering the whole production chain from farm to factory[92]. Another example is the International Seafood Sustainability Foundation (ISSF), a global coalition of fisheries scientists and industry members (https://www.iss-foundation.org/), which has been developing best practice guidelines on non-entangling and biodegradable fish aggregating devices (FADs) that minimize environmental impacts (e.g., reduce shark bycatch and marine pollution) (ISSF, 2019) while advocating for their implementation. Other guidelines for new fisheries-related technologies such as EM systems are also being developed (Restrepo et al., 2018; Murua et al., 2020). The guidelines are living documents which are reviewed regularly and updated when considered necessary. Some best practices are self-imposed by the fishing industry (e.g., Codes of Best Practices adopted by the EU tuna purse seiner fleet; Grande et al., 2020; Maufroy et al., 2020), and have been gradually taken up by RFMOs as part of a bottom-up process. Since fishers and industry were actively part of the solution from the early stages of setting best practices, the acceptance and implementation of such guidelines have been faster and more implementable thanks to the acquired sense of stewardship (Murua et al., 2017; Restrepo et al., 2019). The benefits of fishing industry stakeholder inclusiveness in cooperation processes for setting better sustainability standards has been reported in many cases (Johnson and van Densen, 2007; Stephenson et al., 2018). In recent times, institutions, such as the EU, have also tried to increase fisheries stakeholder representation in decision-making processes (Aanesen et al., 2014; Linke et al., 2020). Nevertheless, not all best practices can be left in the hands of industry, and other stakeholders like fisheries scientists and managers should play a part. This might be the case with the incorporation of novel technologies, where fishers lack technical expertise in the field.

Guidelines and recommendations for best practices have been developed in many fisheries, from small-scale to large scale (Lodge et al., 2007; Rocliffe, 2018; Westlund and Zelasney, 2019; March et al., 2022) and aimed towards different stakeholders including fishers, scientists, and managers. These guidelines cover many aspects (e.g., bycatch mitigation, fishing effort, gear selectivity, marine pollution, social ethics, etc.) across the principal fisheries such as trawling (Grieve et al., 2015; McConnaughey et al., 2020), longline (Løkkeborg, 2011; Bealey, 2021) or purse seine (Hutchinson et al., 2017; Pacifical, 2021). Similarly, ethically, and ecologically sound practice guidelines promoting sustainable actions exist for the aquaculture industry (Tucker and Hargreaves, 2008; Kamaruddin et al., 2015). This shows how the production of best practice guidelines is a general feature across the fishing and aquaculture sector and could provide a reference point for the development of AI guidelines.

4.4.2. The EM example of digitalisation good practices in fisheries

Fisheries monitoring programs are essential for effective management of marine resources, but are very costly due to the need for skilled human observers and are not exempt from errors (Duparc et al., 2019). EM (Ruiz et al., 2015; Gilman et al., 2019). Programs enhanced with automatic species identification (Lekunberri et al., 2021) are of growing interest for industry and managers. EM is a proven technology for fisheries monitoring that has been widely tested and continues to grow, primarily in industrial fleets but with potential applications in smaller vessels. It provides a good example of development that could be useful for AI systems good practice development. An effective EM system should meet several requirements (i.e., Minimum Standards) to guarantee quality and consistency across vendors. All tuna RFMOs have engaged in recent years in the definition and implementation of these minimum standards, with different progress among RFMOs. In the Pacific (WCPFC and IATTC) draft standards have been prepared for the longline and purse seine fisheries, while in the Atlantic (ICCAT) and Indian (IOTC) oceans, minimum standards for the purse seine fishery have been preliminary adopted by the Commission (Ruiz et al., 2016; Ruiz et al., 2017; Román et al., 2020; ERandEMWG4, 2020).

92 https://www.bapcertification.org/Standards

Several EM practices are in place in New Zealand, where invasion of privacy is one of the main concerns raised by fishers. These concerns are addressed by conducting monitoring in vessel areas where only fishing-related activities take place. EM footage is recorded electronically and automatically encrypted. Therefore, only authorised staff can access the footage. This footage allows dolphin interactions with vessels and gears to be identified. A sample of this footage is also reviewed to verify species fish catch composition. The information collected is then compared to fishers' reports. The MPI conducts an impact assessment to identify risks to privacy. Owners and skippers are involved in the process of installation to guarantee full transparency in decisions about location of cameras to ensure that the video footage concerns only fishing activities. The MPI aims to install cameras in more than 300 vessels by 2024, which represents around 85% of the catches starting in late 2022. A vast consultation process about the wider application of EM took place between October 2021 and December 2021. Hence, a wide array of stakeholders had the opportunity to provide insights on the technical and management aspects of this proposal (New Zealand Fisheries, 2021). A tendering process will likely take place to call for expressions of interest concerning AI systems able to analyse the EM footage[93].

In the US, EM was first employed in 2015 in the pelagic longline fishery to monitor bluefin tuna bycatch. EM is currently in place in at least 113 fishing vessels (EDF, 2020). The use of EM was expanded to US tuna longliners under the purview of ICCAT to evaluate whether the shortfin mako shark was released alive. It is expected that EM could provide evidence to reopen fisheries currently closed due to conservation issues. In 2011, a 100% monitoring at sea was implemented in the Pacific ground fisheries. In 2015, EM arose as an alternative to full observer coverage. Video review and storage is carried out by National Fisheries Marine Service (NFMS). The system introduces the 'third-party scheme' which consists in the certification of the providers of hardware, software, installations, etc. These providers have to submit a plan to NFMS to describe how they will provide NFMS with the information necessary for fisheries management. Similarly, to the observer program, the industry will be required to outsource the services through private certified providers. In turn, fishers must prepare a plan for the use of the EM system onboard and obtain certification and guarantee complete identification of catch, continuous vessel location monitoring, recording of any haul, set, or discard event, prevention of radio frequency interference, etc. Consultation is taking place and the program is expected to be fully operative by January 2024 (NOAA, 2021).

At the EU level, the European Fisheries Control Agency published in 2019 sets out guidelines and specifications for the implementation of remote Electronic Monitoring (EM) in EU fisheries (EFCA, 2019). Meant as a guidance document for Member States, it describes minimum technical requirements and standards for EM systems which could be used as a tool to monitor and document compliance with the CFP, and specifically compliance with the LO. Similarly, in 2021 UNE, the Spanish standardization body at the national level, published the UNE 195007:2021. This standard establishes the requirements and technical conditions that must be meet when implementing an EM system in any fishing vessels greater than 12 m. This standard includes the characteristics that the equipment should meet, as well as the requirements for all the operators involved in the electronic observation (fishing vessel owners, technology companies that manufacture onboard equipment and data analysis entities). However, these standards are not considering future use of AI in EM systems and they will need to be adapted. Fortunately, there are AI good practices developed by AI experts that can be used to adapt fisheries guidelines (see next section).

[93] https://www.stuff.co.nz/business/farming/124404842/ai-to-help-protect-endangered-marine-species-but-what-about-fishermens-privacy

4.4.3. AI good practices guidelines useful for development of AI good practices in fisheries

Policy makers should not leave loopholes in regulations that allow undesirable industry actions (Rosenberg and Glass, 2007). For this reason, it is highly recommended that AI best practice guidelines are established in a cooperative and transparent manner between industry, regulators, and the scientific community to set the minimum standards in these early phases of technological adoption. It appears that successful AI guidelines across many sectors share common ethical traits such as transparency, fairness, responsibility, good faith, trust, and sustainability (HLEG-AI, 2019; Ryan & Stahl, 2020; Leimanis & Palkova, 2021; Makarov et al., 2021; Stix, 2021) where the following principles and good practices have been identified:

- AI should be lawful: well-thought out current and future regulations should be established.
- AI should respect human autonomy: AI systems should allow for human oversight, allowing for monitoring of results accuracy and termination. Consequently, the outcome of AI decisions should be reversible. Accountability strategies should be created within companies and individuals should have the possibility to lodge complaints and request justifications on the results from AI systems.
- AI should prevent harm: AI should preserve the quality, integrity, and privacy of the data.
- AI should be fair: all affected stakeholders through the AI system life cycle need to be taken into consideration and be allowed to participate.
- AI should not discriminate: all stakeholders have equal access and treatment without discrimination against individuals or groups of individuals. There should be steps to ensure that data used by AI is not unfair, or contains bias, errors or inaccuracies that can lead to discrimination.
- AI should ensure human rights: developers and organisational users should ensure that AI does not infringe on human rights by ensuring their technology's safety.
- AI should protect integrity: not only physical, but also mental integrity, personal and cultural sense of identity, and satisfaction of people´s essential needs.
- AI with clear use requirements: users need to be notified so they know they are not interacting with another human being.
- AI should protect democratic values: which should not be jeopardised as a result of AI use, and citizens should receive accurate and impartial information without interference or manipulation for political purposes.
- AI should empower and benefit individuals: providing equal opportunities while distributing the rewards from its use in a fair and equitable manner.
- AI should be harmless: designed with the intent of not doing foreseeable harm to human beings
- AI responsibilities should be defined: where developers and users are responsible for errors and harm by AI. Therefore, there needs to be a clear and concise allocation of responsibilities to deal with harm when it occurs.
- AI should show transparency: technical as well as industry capacity and aims should be clearly communicated.
- AI should be technically robust: having suitable fallback plans, reliability, and reproducibility.
- AI should be safe: where attacks against AI should not compromise the bodily and mental integrity of people by ensuring the reliability and internal robustness of the systems (fail gracefully).

- AI systems should improve citizens´ wellbeing: used to respect and better the quality of the lives of citizens
- AI should show accountability: it should report potential negative impacts or trade-offs among other good practices.
- AI should be designed to use little or no personal data: if required, then it should be anonymised, encrypted, and securely processed.
- AI should contribute to the environmental sustainability: contributing to resource efficiency, mitigate emissions and the protection of biodiversity.
- At the core of any AI project should be high quality data that are well-understood, consistent and use FAIR principles. Data should be accurate, up-to-date, and fit-for-purpose. Models should be published with code, training, and testing data along with scientific results.
- Regarding AI safety protocols, a list of prohibited uses should be prepared, and a risk management system set in place as a continuous iterative process through the AI system's lifecycle.
- AI should protect democratic values, which should not be jeopardised as a result of AI use, and citizens should receive accurate and impartial information without interference or manipulation for political purposes.
- In all cases AI models should be combined with human insight. Improving AI-related skill sets among company members is considered important.

4.5. Coordination at the EU level, such as working groups on AI

Several existing or recent working groups on ML and statistical approaches in fisheries and marine sciences at EU and international level, where authors from this study have participated, have been analysed in the following lines to determine possible coordination needs at EU level:

- ICES Working group on ML in Marine Science (WGMLEARN) is led by European organizations, but has a major presence of North American members. This group has been quite active in the last three years, holding two or three meetings per year. However, the rotation of active members has been high, resulting in a reduction of finalized outputs and variable interests of the contributing members. This group has prepared an AI bibliographic database that is regularly improved by members. This group is currently preparing three scientific publications. The group seems to be dominated by experts on image analysis and DL despite attempts to have a broader coverage of expertise.
- The OCB Phytoplankton Taxonomy Working Group is a group leaded mainly by NASA and WHOI in North America. The aim of the group is to establish standards and best practices for submitting taxonomic and morphological information for plankton collected by imaging instruments. The group was very active until mid-2019 with a recent publication defining potential standards in 2021 (Neeley et al., 2021).
- I/ITAPINA: Imagine/Imaging The Atlantic – A Pelagic Imaging Network Approach, is a recently formed group led mainly by European institutions which has organized only a single event in mid-2021. This group work appears to focus more on the technical aspects of image acquisition than on its potential later use by AI algorithms.
- NCAI Community of Practice, promoted by NOAA Centre for Artificial Intelligence, is a community led by the United States National Oceanic and Atmospheric Administration (NOAA). The group also was recently created after a workshop during 2021 and had an event scheduled for February 2022.

- ICES-FAO Working Group on Fishing Technology and Fish Behaviour (WGFTFB) is a group with a technological background that is within the scope of the AI group in fisheries technology despite it not being its principal focus.
- ICCAT: At least two AI studies have been presented and discussed in this forum. In a first study, Uranga et al., (2017) used image analysis of fishers' sonar images and supervised classification to provide data for abundance indices in combination with scientific surveys. In a second study that has not yet been published, the use of AI for a Candidate Management Procedure was attempted. The group expressed that there is potential in such developments, but there was concern with the apparent black box nature of some of the AI methodologies.
- The main objective of ICES ACEGG working group is to evaluate and provide estimates for small pelagic species in ICES sub-Areas 6-9. In relation to the acoustic methodology, multifrequency acoustic studies have shown potential in continuous monitoring. Currently, it is possible to discriminate acoustic scattering groups (as fish with swim bladders, fish without swim bladders, and certain plankton groups) based on its acoustic properties, but visual interpretation or scrutiny by experts is still widely extended. Currently, there are studies aiming to develop AI classification models to identify the pelagic fish species echotraces in the Bay of Biscay.

These relatively few AI working groups that specialise in fisheries reveal the need to coordinate efforts and exchange ideas and experiences identified by the scientific community in this emerging field. However, these AI focused groups are in general poorly coordinated with a short supply of stable members. These scientific groups mostly operate by experts giving their time as an in-kind contribution or as part of ongoing projects that are using or developing AI or generating data that might be useful in AI systems. These projects usually funded travelling for meetings and workshops, but lately with the COVID situation these groups have been meeting remotely. This scarcity of specific funding hinders the long-term commitment of their members and weakens the group's outcomes. Many of the groups have changing agendas and objectives depending on the interests of the principal coordinators. This is likely exacerbated by the dominance of members with a particular AI-related skill set, but with a sparsity of members with multidisciplinary skills. Despite all this, these groups are somewhat effective at increasing the networking of people in the AI field, but on average they yield poorly in terms of actual developments and publications when compared with other working groups. This could be due to a lack of AI expertise in fisheries and competition for AI experts with other industries that also demand AI knowledge and are able to provide more interesting salaries and conditions (e.g., remote work and flexible timetables). Currently, AI experts are few and far between and AI experts with some fisheries knowledge are even harder to find. While developing a simple AI proof-of-concept with some example data might not require deep understanding of fisheries, developing a trustworthy pilot that can be tested in the real environment under commercial fishing conditions requires a deep knowledge of fisheries. This includes understanding all the complexities, limitations, and realities of fishing activities to produce realistic outputs. Moreover, possibly highly technical experts are unlikely to be skilled or interested in writing project proposals or engaging in the long-term process associated with the involvement in these fisheries scientific groups.

Other AI groups of international reference that do not focus on fisheries or marine science have been identified:

- High-Level Expert Group on Artificial Intelligence (AI HLEG). The AI HLEG is an independent expert group that was set up by the European Commission in June 2018. A first draft of this document was released on 18 December 2018, together with the first draft of the AI HLEG's Ethics Guidelines for Trustworthy AI. Its work has helped the AIA proposal formulation. It is not a fisheries, marine, or environmental focus group.

- The European AI Alliance[94] is a platform for providing feedback to AI HLEG, to share AI documents and events. There were two major events in June 2019 and October 2020.
- The European Network of AI Excellence Centres (ELISE): This is a network of institutions working on data-driven learning and builds on top of and in collaboration with the ELLIS Society (European Laboratory for Learning and Intelligent Systems). The main activities seem to be exchanges and training of researchers.

These groups could be a good opportunity for training fisheries scientists and industry in AI technologies, but they have the partial disadvantage of a lower understanding of the marine environment and its data characteristics than the previous list of groups. This fit-for-purpose knowledge is critical for successful application of AI in fisheries. There is an alarming number of technological companies without sufficient previous experience trying to sell AI developments to the fisheries industry and scientists, which might not be adapted to the reality of this sector. We have discussed in previous sections how ML has already proven its potential in marine sciences. However, if AI methods are not fit for purpose, then trade-offs necessary to accomplish appropriate performances can be missed (Fernandes et al., 2009) or overfitting without robust validation can lead to over confidence in AI capacities (Fernandes et al., 2010). A multi-disciplinary approach where the domain experts and AI experts work together is key for enabling this fit-for-purpose AI that can go beyond the state-of-the-art in more than one discipline (Fernandes et al., 2013; Hernández-González et al., 2019). As combining leading class experts in AI and fisheries might not be feasible in all instances, an intermediate approach can be employed to enable greater progress. An example may be training a marine ecologist or other marine biology/fishery expert who is interested in statistics and ML (Grosjean et al. 2004; Fernandes et al., 2012; Trifonova et al., 2015; Uusitalo et al., 2016), or a person with a computing or statistical background with an interest not only in theoretical algorithms but also in their application to fisheries and other marine issues.

[94] https://digital-strategy.ec.europa.eu/en/policies/european-ai-alliance

5. CONCLUSIONS AND RECOMMENDATIONS

KEY FINDINGS

- Main opportunities identified are: 1) increased transparency of fishing activity and reduced impact on the environment, thereby improving the public image of the sector; 2) early warning, forecasting and spatial planning systems can help in the planning activities considering trade-off between them; 3) accelerated and increased data acquisition and coverage for stock assessments, sustainability indicators evaluation and other management data needs; 4) increased economic sustainability of the fishing industry, by reducing operational costs; and, 5) the modernisation of fisheries and its subsequent attractiveness to the younger population.

- Main obstacles identified are: 1) industry trust and reluctance; 2) initial costs and lack of expertise; 3) legal and bureaucratic uncertainty.

- AI can increase efficiency and reduce costs for industry, but there are important barriers such as developing and installation costs, the scarcity of standards, and a lack of multidisciplinary expertise (biological, AI and legal) to develop fit-for-purpose systems.

- Although some AI approaches are considered black boxes (e.g. Artificial Neural Networks (ANNs)), there are other suitable AI methods to understand the basis, processes and model forecasts and their uncertainty (e.g. Bayesian Networks (BNs).

- Policy recommendations relevant to EU decision-making to achieve a better use of AI systems in the fisheries sector are: 1) add AI references to fisheries legislation and AIA proposal; 2) regulate the role of technological companies; 3) promote multidisciplinary academia and professionals; 4) regulate the role of AI technological providers, ensuring some degree of experience in fisheries to prevent untrustworthy and not-fit-for-purpose AI systems; 5) develop AI good practices guidelines for fisheries; 6) create incentives for the development and use of fit-for-purpose fisheries AI systems; 7) improve and promote public and private data sharing; and, 8) promote awareness and collaboration with fisheries sector.

5.1. Analysis of the impacts of AI use in the fisheries sector: opportunities and obstacles

The use of AI for fisheries confers important benefits to the fisheries industry, scientists, and policy managers thanks to the ability of these methods to quickly process large data from different sources and with different formats, interpret the inputs and provide advice for improved results. The following main advantages of AI use in fisheries have been identified:

- AI can help to reduce the impact of fisheries on the environment (e.g., emissions, bycatch and discards) while reducing operational costs for the industry and improving the public image of the industry.
- Early warning, forecasting and spatial planning systems can be developed using AI methods, even under high uncertainty, to assist industry and managers in their planning activities, mainly when trade-offs between activities, impacts and potential benefits need to be considered.

- AI system can accelerate and increase data acquisition and coverage for stock assessments, sustainability indicators evaluation and other management data needs.
- Some AI approaches are considered black boxes (e.g., ANNs) where it is difficult to understand the reasons behind the model predictions. However, other AI methods are more suitable to understand model forecasts and their uncertainty (e.g., BNs).
- Method standardization for results integration and comparison are needed to understand the performance of AI systems among providers.
- AI use can increase fishing activity transparency and public perception, increase the economic sustainability, and reduce waste in the full supply chain.
- Modernising fisheries, with the introduction of new technologies, such as AI, will help to make the fishing industry more attractive to the current and next younger generations.

About the obstacles, there are some limitations to the use of AI systems that are inherent to their reliance on data availability. For instance, in a public consultation[95], the main barriers to data sharing identified where: 1) legal uncertainty due to different rules in Member States; 2) legal barriers in the use of business data for the public interest, including competition rules; 3) lack of commercial incentives to share data; 4) lack of awareness of related data bases or platforms; and, 5) lack of assurance that the data will only be used for the public interest purpose for which it was requested. Another barrier could be that companies may feel that with the AI their know-how can be exposed to competitors or other third parties. There is a fear in the fishing sector (and other industries) that data provided for AI will not only be used for the public interest purpose for which it was requested. Furthermore, there is perhaps a sense by fishers that with AI they lose the privacy and ownership of their day-to-day working data. Moreover, fishing industry is quite conservative in their approaches and some members might be unwilling to voluntarily embrace changing technologies. Misuse of AI tools leading to overexploit resources or misbehaviour is a general worry by fisheries managers and environmental organisations. A frequent concern with AI is the fear that there will be too much reliance on decisions taken by automated systems, with little human supervision and proper ground truth verification. For example, if erroneous AI-based fisheries interpretations based on poorly designed algorithms go unchecked by experts in the field it could lead to ineffective management measures. The costs associated with initial implementation of AI technologies can be a concern for fishing companies, particularly for small-scale artisanal members. In some cases, it might help that governmental bodies provide direct or indirect economic incentives that favour AI adoption. As AI technology becomes more affordable, it could even be more cost-effective than non-AI options. Finally, some fishers fear that AI might bring about new more rigid and inflexible regulations that can have deleterious consequences on their economic status. The reality of AI in fisheries is that there is still much doubt on its potential overall repercussions. In part, this could be due to the still not very formalized integration of science, regulatory authorities, and the fishing industry, which could help to clarify each stakeholders' role and position within this new field.

5.2. Policy recommendations for the best use of AI in the fisheries and its value chain

This study team, based on the literature reviewed, their own expert knowledge and the stakeholder surveys, suggest the following policy recommendations:

95 Summary report on the public consultation on data act and amended rules on the legal protection of databases. Available at EC portal: https://ec.europa.eu/newsroom/dae/redirection/document/81599

1. Amend Regulations that are or will be subject to revision in this field to include a reference to AI systems and AIA definition in paragraphs where digital transformation and new technologies are mentioned.
2. Amend the AIA proposal to include fisheries sector. Its Recital 3 currently reads "[…] in healthcare, farming, education […]", it could be amended to "[…] in healthcare, farming and fishery, education […]".
3. Promote formation of interdisciplinary fisheries experts with AI related skills and multidisciplinary teams (e.g., AI, biological, economic, and legal disciplines).
4. Find ways to incentivise job opportunities and promotion of multidisciplinary and interdisciplinary experts not only in academia but also in the private fishery sector.
5. Attract new young workers and empower women with AI skills in fisheries sector jobs through dissemination of information programs and by providing adequate incentives.
6. Promote private data collection and sharing, including appropriate data aggregation and anonymization safety protocols to facilitate industry trust.
7. Support the development of good AI practices and standards for statistical validation and ground truth verification to increase consumer and industry trust in AI performance, also supported by strong science fit-for-purpose applications aligned with sustainability goals.
8. Regulate the role of AI technological providers, ensuring some degree of experience in fisheries to prevent untrustworthy and not-fit-for-purpose AI systems (e.g., establishment of audited registration programs).
9. Create regulations limiting the access of certain kinds of AI systems to the fisheries sector to help avoid their application in illegal or unethical activities (e.g., through regional fisheries management organisations (RFMOs) or registers for vessel compliance with sustainability practices from trustworthy organisations).
10. Support the development of good AI practice guidelines in fisheries through collaboration with stakeholders and organisations (e.g., RFMOs, certification agencies, NGOs) using mechanisms and principles proven to be successful in other types of fisheries best practices guidelines.
11. Promote AI awareness, both benefits and constraints, among managers and industry to improve adoption processes at the whole chain (e.g., faster data provision in stock assessment, near real-time quota monitoring or agile product traceability).
12. Promote collaboration between universities, firms, AI developers and other stakeholders in fisheries (e.g., though specific funding, specialized centres, and multidisciplinary networks).
13. Promote technological development integrated with AI systems to develop more selective fishing gears and fishing strategies (e.g., better camera systems, wireless communication for real-time control, etc.) by funding AI research and vessels digitalisation.

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This study reviews current artificial intelligence (AI) systems legislation, the AI techniques definition proposed by the AI Act and main applications of AI methods in the fisheries sector with special focus on applications to enhance traceability of fishery products, fishing gear selectivity, good practices, and potential to help young people finding jobs. Finally, this study offers policy recommendations relevant to EU decision-making to achieve a better use of AI systems in the fisheries sector.

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