Degree of implementation of the different technological areas that make up Aquaculture 4.0 in the European aquaculture production sector and the needs and demands of companies for the coming years in this technological field

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1. Executive Summary

The report provides information on the degree of implementation of Aquaculture 4.0 in the European aquaculture production sector. It includes a scientific review of the technological areas that make up Aquaculture 4.0.

New technologies were classified into different groups.

A survey about the implementation of these new technologies was addressed to aquaculture producers in different countries.

With the results of this survey, the consortium will be able to face the next tasks and prepare contents related with Aquaculture 4.0 for Vocational Training.

The report highlights the challenges facing companies in adopting new technologies and provides a recommended bibliography and survey results in the appendices.

The work carried out will be helpful to impulse the aquaculture sector into the future and to prepare it to face the important challenges that are awaiting

2. Detailed report on the deliverable

2.1. Background/Introduction

This report is the deliverable for T2.1. "Degree of implementation of the different technological areas that make up Aquaculture 4.0 in the European aquaculture production sector and the needs and demands of companies for the coming years in this technological field". The task T2.1 is part of the work carried out in the WP2 of the Project "Approach to digitisation, collection of good practices and training programmes of the aquaculture sector to be digitized".

The main objectives of this WP2 are:

- To study the degree of implementation of the different technological areas that make up Aquaculture 4.0 in the European aquaculture production sector and the needs and demands of companies for the coming years in this technological field.
- To draw up a new structure for the training course, defining priorities and dissemination activities.
- To identify the topics where digitisation will be most appropriate.
- To evaluate the reinforcement of business opportunities using advanced digital tools
- To identify the needs and opportunities for Vocational Training, detecting meeting points with Producers' Associations and transferring possibilities for an official Curriculum at European level.

2.2. Description of work

The work has been led by the UCH-CEU, and in collaboration with UAlg, UNIBO, RTEU, MARE and CCMAR has carried out a research on the level of implementation of new technologies in the partner countries.

The parts of the job developed have been:

- Scientific documentary research, analysis of reports from public bodies on the subject of study.
- Preparation of a specific questionnaire to be sent by the partners to their associates.
- Collection and analysis of data.
- Preparation of a report on results.

E-SCH.EG has worked on the design of the questionnaires, and the Business associations API, APA and AMA distributed it to their members.

2.2.1. Scientific review

2.2.1.1. Introduction

Aquaculture in the EU and worldwide

According to the Food and Agriculture Organisation of the United Nations (FAO), global production of aquatic resources in 2021 totaled 218 million tons, representing an increase of 2.0 % compared to the previous year, 2020. Extractive fisheries contributed 92 million tons, representing 42.3 % of the total, while aquaculture contributed 126 million tons, equivalent to the remaining 57.7 %. (APROMAR, 2022).

It is important to note that since 2017, the production of aquatic resources has maintained a constant level above 200 million tons. In the same year, an increase in production volume of 4.1 % was observed compared to the previous year, reaching 198.9 million tons in 2016 (APROMAR, 2022).

The overall European aquaculture-based fish production for the year 2020 is estimated to reach 2,570,650 tons. This figure suggests a modest increase of 2.8 % in total production compared to the previous year, 2019. Among this production, marine cold-water species make up the majority at 70 %, freshwater species account for 14 %, and marine Mediterranean species constitute the remaining 16 % (FEAP, 2022).

Norway maintains its position as the leading European producer, contributing 58 % of the total output. Their primary contributions include salmon and sizeable trout production (over 1.2 kg). Other nations that annually produce over 100,000 tons include Turkey, the United Kingdom, and Greece. The primary species in production are salmon, trout, seabream, seabass, and carp, collectively accounting for 95 % of Europe's total production in 2020 (FEAP, 2022).

The European Union (EU-27) emerges as the leading and most prominent global market for aquatic products. In 2022, per capita consumption of aquatic products in the EU stood at 21.1 kilograms in terms of whole fish, in contrast to the 22.6 kilograms recorded in 2021, representing a 7.1% decrease from the previous year, according to AIPCE reports (APROMAR, 2022).

During 2022, the EU (27) produced a total of 4.6 million tons of aquatic products, combining fishing and aquaculture. Of this figure, 2.1 million tons were exported, and 1.1 million tons went to non-food uses. In addition, 8.55 million tons of aquatic products were imported and 2.2 million tons were exported, meaning that the total supply for consumption reached 9.4 million tons in 2022. As a result, the self-sufficiency rate stood at 33 % (APROMAR, 2022).

In the same year, dependence on imported aquatic products reached 67%, mainly due to a decrease in catches from extractive fisheries. The average apparent per capita consumption of aquatic products in the EU (27) was 23.3 kg (live weight) per person per year in 2020, which marked a decrease of 7 % compared to the previous year (APROMAR, 2022).

Challenges for the European aquaculture sector

As all other sectors, the livestock industry faces different challenges such as animal health and welfare, the environmental impact, ensuring the safety and quality of food products, and addressing the issue of zoonotic diseases. Additionally, there is an increasing demand for animal products, while the number of farmers is declining. This has resulted in much bigger herds per farmer, making it difficult to manage the farms, and the appearance of diseases. (Berckmans, 2017).

The aquaculture industry faces problems such as labor-intensiveness, environmental pollution, diseases, and lack of traceability of products. These limitations can be addressed by using modern types of technologies, such as Industry 4.0-based smart systems, to achieve sustainable and profitable production (Biazi & Marques, 2023).

Some authors highlight the critical issue of incorporating the costs of environmental goods and services into aquaculture production economics. Most aquaculture systems rely on low-cost or no cost environmental resources, and addressing this challenge is crucial for the future sustainability of the sector (Bostock et al., 2010; C. Wang et al., 2021).

Disease management is also a significant challenge in aquaculture. The impact of salmon lice on both wild salmonids and salmon aquaculture is discussed, emphasizing the need to identify effective candidates for commercial vaccines to mitigate the effects of these parasites (Torrissen et al., 2013; C. Wang et al., 2021).

Technological advancements play a crucial role in addressing the challenges of the aquaculture sector. Genome editing can improve aquaculture breeding and production. This technology offers opportunities for enhancing traits related to disease resistance, growth, and environmental adaptation in farmed fish (Gratacap et al., 2019).

What is the Aquaculture 4.0

To give a solution to the challenges faced by the livestock industry, the Precision Livestock Farming provides some solutions to help monitor animal health and welfare by providing real-time data on individual animals, allowing farmers to detect and treat health issues early. This approach can also help reduce the environmental impact by optimizing feed and water usage, reducing emissions, and improving manure management. Additionally, can help ensure the safety and quality of food products by providing traceability and transparency throughout the supply chain. Finally, PLF technology can help address the issue of zoonotic diseases by providing early detection and prevention measures (Berckmans, 2017).

Precision Livestock Farming provides real time monitoring and management systems for farmers. This approach is different from other approaches that rely on human experts scoring animal-based indicators. The main aim of this technology is the early detection of problems and the immediate management action to improve animal welfare and productivity (Berckmans, 2017).

The Precision Livestock Farming requires the application of different expert areas such as animal science, engineering, computer science, and data analytics. This interdisciplinary team, working together, can develop and implement these technologies to improve the animal production (Berckmans, 2017).

Aquaculture 4.0, also known as precision aquaculture, is the application of Fourth Industrial Revolution technologies to the aquaculture field. These technologies encompass artificial intelligence, big data analytics, machine learning, computer vision, and automation. Their integration is aimed at enhancing the efficiency, productivity, and sustainability of aquaculture operations (Mustafa et al., 2021).

Precision aquaculture is a vital element within the aquaculture industry, playing a key role in its progression and long-term sustainability. It involves the adoption of cutting-edge technologies, data-driven approaches, and innovative methods to optimize production, enhance efficiency, and mitigate environmental impacts (O'Donncha & Grant, 2020).

The concept of " replacing human with machine " finds application in the realm of intelligent fish farming, where modern technology is harnessed to automate functions like oxygen enhancement, feeding optimization, disease prevention, and precise harvesting. This automation enables precise and efficient operations, liberating human power entirely while fostering environmentally-friendly and sustainable aquaculture practices. The incorporation of intelligent digital technologies, agricultural robots, IoT, edge computing, 5G, and artificial intelligence algorithms can collectively advance the field of intelligent fish farming. The ultimate objective is to establish fully autonomous, unmanned fish farms that rely on cutting-edge technology for their operation. (C. Wang et al., 2021).

One of the key areas where Aquaculture 4.0 can make a significant impact is in disease management. The use of emerging diagnostic technologies, such as deep learning and computer vision, can enhance disease detection and monitoring in aquaculture systems. These technologies enable early detection of diseases, allowing for timely intervention and prevention of disease outbreaks (Dong et al., 2023).

Another important aspect of Aquaculture 4.0 is the use of smart aquaculture systems. These systems leverage machine learning and computer vision to optimize various aspects of aquaculture operations, including live fish identification, species classification, behavioral analysis, feeding decisions, and water quality prediction. By automating and optimizing these processes, smart aquaculture systems can improve production efficiency and reduce environmental impacts (Vo et al., 2021; Yang et al., 2021).

Furthermore, Aquaculture 4.0 can contribute to the sustainable development of the aquaculture industry. The integration of its technologies can enable precise and data-driven management of aquaculture systems, leading to better resource utilization and reduced environmental impacts. For example, by using big data analytics and predictive modeling, aquaculture operators can optimize feed formulation and feeding strategies, minimizing waste and improving feed conversion efficiency (Mustafa et al., 2021).

In addition, Aquaculture 4.0 can facilitate the expansion of aquaculture into new areas, such as offshore environments. Smart spatial planning, supported by advanced technologies, can mitigate potential negative effects of offshore aquaculture and ensure sustainable development. By optimizing the use of space and minimizing environmental impacts, offshore aquaculture can unlock untapped potential for seafood production.

Overall, Aquaculture 4.0 represents a paradigm shift in the aquaculture industry, leveraging advanced technologies to enhance productivity, sustainability, and resilience. By integrating Fourth Industrial Revolution technologies into aquaculture operations, the sector will address key challenges and unlock new opportunities for the future of aquaculture.

2.2.1.2. Objectives

The aim of the review are:

- To perform a systematic review of the scientific about the aquaculture 4.0 technologies.
- To prepare a survey to collect data about the level of implementation of aquaculture 4.0 technologies in the countries participating in the project.
- To analyze the data collected from the survey.

2.2.1.3. Material and methods

Different sources of information were used: Pubmed, Google Scholar, ResearchGate.

The first step was to look for articles with the keywords "Aquaculture 4.0", "Precision aquaculture" and "Smart aquaculture", prioritising those articles that are a bibliographical review. Articles about precision farming or precision livestock were also reviewed.

From these articles, a selection of the main technologies related to aquaculture 4.0 was made.

The keywords used were: aquaculture, 4.0, precision, smart, IoT (Internet of Things), robotics, UAV, ROV, blockchain, intelligent sensing and combinations. Table 1 shows the results of the different keywords used in Pubmed, that is the most widely used search engine for scientific knowledge.

Table 1. Keywords used and results obtained in PubMed.

Keywords	Pubmed
Aquaculture + 4.0	317
Aquaculture + precision	586
Aquaculture + smart	153
Aquaculture + IoT	25
Aquaculture + robotics	28
Aquaculture + UAV	8
Aquaculture + ROV	10
Aquaculture + blockchain	3
Aquaculture + intelligent sensing	15

The abstracts of the articles obtained were read, selecting those that were directly related to the topic under study. Many of the articles found, for example in the search for "Aquaculture+4.0" gave results that had nothing to do with the topic of the study.

In addition, the cited references in the reviewed articles were checked, checking those articles that were not included in the initial review.

The European Commission website was also used to search for Horizon 2020 projects related to aquaculture. It was filtered by the term "Aquaculture", obtaining a total of 362 projects. The information on these projects was reviewed, selecting those related to aquaculture 4.0.

15 projects were selected for its relevance and relationship with this project:

- Tools for Assessment and Planning of Aquaculture Sustainability.
- Co-creating a decision support framework to ensure sustainable fish production in Europe under climate change
- Intelligent Fish feeding through Integration of Enabling technologies and Circular principle.
- Sustainable Farming for Effective Aquaculture.
- High Resolution Copernicus-Based Information Services at Sea for Ports and Aquaculture.
- New Technologies, Tools and Strategies for a Sustainable, Resilient and Innovative European Aquaculture.
- Developing Innovative Market Orientated Prediction Toolbox to Strengthen the Economic Sustainability and Competitiveness of European Seafood on Local and Global markets.
- Intelligent management system for integrated multi-trophic aquaculture.
- Enabling Precision Aquaculture with multi-variable real-time sensing and Copernicus Earth Observation data.
- Smart System for the Prevention of Biofouling on Aquaculture NETs by Ultrasonic Wave Technology.
- Aquaculture Smart and Open Data Analytics as a Service.
- The European first generation of aquaculture SERS-based Biosensor.
- Development and evaluation of miniaturized biosensors for diagnosis of pathogens in aquaculture.
- Continual Acoustic Based Multifunctional Cage Mounted Fish Estimator Deigned To Reduce Feed Waste, Fish Mortality, and Predator and Fish Escape Control.
- ECO-INNOVATE-AQUACULTURE-SYSTEM.
- Smart Feeding Systems for Hatcheries: Automatic central feeding system of live food and micro diets for farmed fingerlings.

In the case of these projects, the results obtained were reviewed and the related scientific articles were added.

Over 200 documents were selected and studied, including articles, abstracts of conference papers, reports and projects information. The recommended bibliography can be found in the Appendices.

2.2.1.4. Results of the scientific review

There are many different technologies that can be applied to Aquaculture 4.0. We can distribute in different categories:

- Internet of Things,
- Robotics
- Camera systems,
- Support tools for decision making,
- Modern sensing techniques,
- Blockchain technology,

Internet of Things (IoT)

Aquaculture farms can benefit from various applications of the Internet of Things (IoT) technology. One important application is water quality monitoring. IoT-based systems can collect real-time data on parameters such as temperature, pH, dissolved oxygen, and nutrient levels in aquaculture systems. This data can be transmitted wirelessly to a central monitoring system, allowing farmers to continuously monitor and analyze the water quality. By detecting any deviations from optimal conditions, farmers can take timely actions to maintain a healthy environment for the aquatic organisms and prevent potential issues (H. R. Lim et al., 2022; L. W. K. Lim, 2023).

Another application of IoT in aquaculture is fish monitoring. IoT-based devices can be used to track and monitor fish behavior, growth, and health parameters. These devices can collect data on factors such as feeding patterns, swimming activity, and water temperature preferences. By analyzing this data, farmers can gain insights into the well-being of the fish and make informed decisions regarding feeding regimes, disease prevention, and overall farm management (Tamim et al., 2022).

IoT technology also plays a role in farm monitoring and management. Unmanned systems, such as drones and autonomous underwater vehicles, equipped with IoT sensors, can be used to monitor aquaculture farms. These systems can capture aerial or underwater images, collect data on water quality, and even detect fish biomass. The collected data can provide valuable information for farm management, including optimizing feeding strategies, identifying areas of concern, and assessing the overall performance of the farm (Ubina & Cheng, 2022).

Furthermore, precision aquaculture, enabled by IoT, involves the integration of various sensors and devices in aquaculture systems. These interconnected sensors can monitor parameters such as water quality, feeding behavior, and environmental conditions. The data collected from these sensors can be analyzed to optimize production processes, improve resource efficiency, and enhance overall farm performance (O'Donncha & Grant, 2020).

The use of **Global System for Mobile** (GSM) is an interesting example of a technology that offers several benefits and applications to the aquaculture sector.

Remote monitoring of plant and water quality parameters, as well as security systems for aquaculture facilities. GSM technology enables wireless communication and remote access, enhancing the efficiency and effectiveness of aquaculture operations (Jawad et al., 2017).

The use of GSM technology has been used, linked with predictive models, to estimate the accumulation of taste taints in RAS-farmed fish, such as geosmin and MIB, based on environmental factors (Hathurusingha & Davey, 2014).

Furthermore, the use of GSM technology can enable the design of smart biofloc monitoring and controlling systems using the Internet of Things (IoT). This allows farmers to remotely monitor and control parameters such as dissolved oxygen, pH, and nutrient levels in the biofloc system, optimizing the conditions for the growth of the cultured organisms (Crab et al., 2012; Tasnim et al., 2022).

Aquaculture farms can benefit from both **on-site and remote interfaces** for various purposes. On-site interfaces allow for direct monitoring and control of the aquaculture system, while remote interfaces provide valuable information about water quality, site selection, and spatial-temporal distribution.

The use of Arduino development environment can also be applied to aquaculture. This technology can also be combined with the use of GSM technology to monitor the aquaculture systems, connecting the circuits to sensors for monitoring parameters such as pH, temperature and humidity (Bakar et al., 2022).

On-site interfaces enable real-time monitoring of those water parameters that need to be continuously monitored and controlled, such as dissolved oxygen, temperature, pH level, and turbidity, allowing farmers to make necessary adjustments to maintain the health and productivity of the aquaculture system (Su et al., 2020).

Remote sensing can also be used to monitor raft aquaculture areas, providing objective information about aquaculture development and land-use changes. It also can be used to study shellfish-farming ecosystems and manage aquaculture operations (Cui et al., 2019; Gernez et al., 2017).

Both on-site and remote interfaces can be combined. On-site interfaces allow for immediate response to changing conditions, while remote interfaces provide a broader perspective and objective information about the aquaculture system. For example, remote sensing data can be used to identify susceptible areas for aquaculture operations based on characteristics such as proximity to discharge, shallow depths, and slow currents. This information can inform the spatial planning of aquaculture farms, reducing the risk of negative impacts on the environment (Gentry et al., 2017).

As it has been already stated, **Water quality sensors** are essential for maintaining optimal conditions for the growth and health of aquatic organisms, ensuring high productivity and quality in aquaculture operations (Kassem et al., 2021; X. G. Liu et al., 2021; Su et al., 2020; C. Wang et al., 2021).

By continuously monitoring water quality, aquaculture farmers can take timely actions to address any issues and maintain optimal conditions. Water quality sensors provide valuable data that enables farmers to adjust feeding rates, manage aeration systems, optimize water exchange, and implement appropriate treatment strategies (Kassem et al., 2021; Su et al., 2020).

Moreover, water quality sensors can contribute to sustainable aquaculture practices. They help minimize the environmental impact of aquaculture operations by preventing the release of excess nutrients and pollutants into surrounding water bodies. By monitoring water quality parameters, farmers can ensure that their practices align with regulatory standards and promote environmental stewardship (Kassem et al., 2021; Liu et al., 2021).

The integration of water quality sensors with advanced technologies such as Internet of Things (IoT), artificial intelligence, and remote monitoring systems further enhances their effectiveness. These technologies enable real-time data collection, analysis, and remote access to water quality information, allowing farmers to make informed decisions and respond promptly to any changes or emergencies (Hassan et al., 2016; Kassem et al., 2021; Liang & Juang, 2022; Sun et al., 2023).

In the aquaculture farms, the monitoring of the animal behavior es crucial. This can be done with **Fish behavior sensors** that provide valuable insights into the state and behavior of fish, allowing for improved profitability and reduced risks of disease and stress incidents (Hassan et al., 2016; Saberioon et al., 2017; Tamim et al., 2022; Ubina & Cheng, 2022).

Machine vision systems have also been applied in aquaculture to monitor fish behavior. These systems utilize computer vision techniques to analyze fish movement and behavior patterns, providing valuable information for fish health and welfare assessment. Also stereo-vision systems and other automated technologies can be used to monitor and manage health and welfare in aquaculture farms (Barreto et al., 2022; Saberioon et al., 2017).

Cortisol stress response in fish can also be measured using sensors, providing insights into the impact of husbandry conditions on fish welfare. By monitoring stress levels, aquaculture operators can make informed decisions to optimize production and minimize stress-related issues (Pavlidis et al., 2013).

By detecting unusual behaviors and identifying potential threats, **early warning monitoring** systems can provide valuable insights and enable prompt action to mitigate risks. These systems can also help prevent the spread of diseases and minimize economic losses (Biswas & Sakai, 2014; Yang et al., 2021).

By observing fish behavior, researchers can identify abnormal patterns that may indicate stress, disease, or other issues. This nondestructive method allows for continuous monitoring and provides an early warning of fish status (Yang et al., 2021).

Different technologies (passive samplers or forecasting models) have been developed to predict the occurrence of toxic harmful algae providing valuable information for the shellfish aquaculture industry (Davidson et al., 2021; Fernandes-Salvador et al., 2021; Pizarro et al., 2013).

Remote water quality monitoring systems with early warning capabilities have been developed for marine aquaculture. These systems utilize various communication media, such as email, SMS, and applications, to provide real-time information on water quality parameters, enabling prompt actions to be taken to maintain optimal conditions for fish health and growth (Pramana et al., 2021).

Robotics

Robotics has emerged as a valuable technology in the field of aquaculture, offering numerous benefits and applications. The use of robotics in aquaculture enables advancements in various areas, including fish locomotion, sensor payload development, underwater object detection, water quality monitoring, and automation(L. W. K. Lim, 2023).

Different types of vehicles, such as **ROV (Remotely Operated Vehicle)** and **AUV (Autonomous Underwater Vehicle)** are both types of underwater robots used for various underwater tasks, but they differ in how they operate and their level of autonomy:

ROVs are typically connected to a surface vessel through a cable that provides power and communication. This allows operators to have direct control over the vehicle's movements and actions, making them suitable for tasks that require precise manipulation and intervention, such as underwater inspections, maintenance, and repairs. ROVs are commonly used in various applications, including offshore oil and gas exploration, scientific research, and aquaculture (Capocci et al., 2017).

In summary, ROVs are remotely operated, requiring a tether and human control, whereas AUVs operate autonomously, following pre-programmed instructions. The choice between the two depends on the specific tasks and objectives of the underwater mission.

One significant application of robotics in aquaculture is the study of fish locomotion. Researchers have developed robotic platforms that mimic the swimming behavior of fish, allowing for a better understanding of their performance and kinematics. These platforms enable the exploration of the swimming capabilities of different fish species, which can inform the design of more efficient aquaculture systems (Zhu et al., 2019).

Sensor payload development is another area where robotics plays a crucial role in aquaculture. The evolution of hybrid aerial underwater robotic systems (HAUCS) has enabled the integration of various sensors for data collection in aquaculture environments. These sensors can provide valuable information about water quality, temperature, pH levels, and dissolved oxygen content, allowing farmers to monitor and maintain optimal conditions for the cultured organisms (Den Ouden et al., 2022).

Underwater object detection is essential in aquaculture for automatically identifying and locating seafood. Robotics, combined with computer vision techniques, can facilitate the development of efficient and accurate underwater object detection systems. These systems can improve the efficiency and safety of fishing operations by automating the identification and tracking of aquatic organisms (Wu et al., 2022).

Robotics can be used to develop lightweight and portable water quality detection robots hat collect real-time data on parameters such as temperature, pH value, and dissolved oxygen content (Huang et al., 2020).

The use of cloud-based autonomous drones in aquaculture systems provides a cost-effective alternative to expensive surveillance systems and multiple fixed-camera installations. These drones can capture visual data and transmit it to cloud-based services, allowing for real-time monitoring (Ubina et al., 2021).

Automation is another significant benefit of robotics in aquaculture. Automation reduces the need for manual labor and enables continuous monitoring and control of essential parameters, leading to increased efficiency and productivity in aquaculture operations (Von Borstel et al., 2013).

Camera systems-based applications and solutions.

The use of cameras in aquaculture has been explored in different contexts, including feeding facilities, security systems, fish welfare, water quality monitoring, and spatial mapping of aquaculture facilities.

For many years, **surface camera** systems have been used mainly for security purposes, both in marine and inland environments.

The use of **underwater video cameras** has expanded in the last years, mainly for feeding purposes. Underwater cameras can also be used to monitor feeding activity and behavior in farming systems such as recirculating aquaculture systems. This allows farmers to assess the health and well-being of the fish, detect any abnormalities or signs of stress, and make informed decisions regarding feeding strategies and environmental conditions (Barreto et al., 2022).

However, the cameras and machine learning classification have demonstrated a big potential for addressing questions of marine animal behavior, distributions, and large-scale spatial patterns. Optical sensors and machine vision systems provide the possibility of developing faster, cheaper, and noninvasive methods for in-situ and after-harvesting monitoring of quality in aquaculture. Underwater cameras are also promising tools for detecting rare freshwater minnows (Bilodeau et al., 2022; Boom et al., 2014; Castañeda et al., 2020; Chang et al., 2022; Marini et al., 2018; Saberioon et al., 2017).

Cameras can also be combined with other technologies to achieve other objectives. For monitoring water quality in aquaculture, can be used in combination with unmanned aerial vehicles (UAVs) equipped with cameras for dynamic inversion of inland aquaculture water quality. The images captured by the cameras are analyzed using spectral analysis techniques to rapidly monitor water quality parameters such as turbidity and chlorophyll concentration (C. Wang et al., 2021).

Image processing techniques have become increasingly important in aquaculture for various applications, including fish detection, behavior analysis, water quality monitoring, and mapping of aquaculture areas. Several references provide insights into the use of image processing techniques in aquaculture:

Stereo-video camera systems have been employed for **three-dimensional monitoring** of fish in aquaculture farms. This system enables the assessment of fish behavior, growth, and overall health in a non-invasive manner, for example monitoring the Pacific bluefin tuna swimming freely in a net cage (Torisawa et al., 2011).

In the context of spatial mapping, cameras, along with remote sensing technologies, can be utilized to map and monitor aquaculture facilities, combined with the use of object-based image analysis (OBIA) to extract coastal aquaculture areas from high-resolution imagery. This approach allows for accurate and periodic mapping of aquaculture facilities, supporting management and planning efforts (Fu et al., 2019).

Image processing and analysis techniques can be applied for non-extractive and non-lethal data collection in fisheries. These techniques enable fish size measurement, catch estimation, regulatory compliance, species recognition, and population counting, providing valuable information for aquaculture management (G. Wang et al., 2019).

Image processing can also be used for automatic counting methods in aquaculture farms. The advancements in sensor technology, computer vision, and acoustic technologies that have enabled efficient and accurate counting methods in aquaculture operations (H. Liu et al., 2023).

Hyperspectral image processing has gained significant attention in aquaculture for various applications, including water quality monitoring, disease detection, and species classification. Several references provide insights into the use of hyperspectral image processing in aquaculture:

Methods and algorithms used for analyzing hyperspectral data, including preprocessing, feature extraction, and classification techniques can improve the monitoring and management of aquaculture systems (Plaza et al., 2009).

The use of remote sensing approaches, including hyperspectral imaging, has been used for monitoring mangrove species in aquaculture, allowing advancements in computer vision, pattern recognition, and artificial intelligence technologies that have improved the discrimination of mangrove species (Pham et al., 2019).

The integration of image processing with **computer vision technology** techniques to enable automated and accurate diagnosis of fish diseases, which is crucial for disease management in aquaculture (Li et al., 2022).

Machine vision systems, combined with optical sensors, offer non-invasive and cost-effective methods for monitoring the quality of aquaculture environments. The use of computer vision, sensor networks, and robotics for animal and environmental monitoring is also important in precision aquaculture (Saberioon et al., 2017; Vecchio et al., 2023).

Computer vision system can also be used for image processing techniques and linear models to measure fish length and predict body weight, providing a non-invasive and efficient method for assessing fish growth (Tonachella et al., 2022).

Camera systems have become increasingly important in aquaculture, offering various applications and solutions. Deep learning techniques combined with optical sensors and machine vision have the potential to provide faster, cheaper, and noninvasive methods for in situ monitoring and post-harvesting quality monitoring in aquaculture (Yang et al., 2021). This technology enables the development of systems that can accurately assess the health and condition of aquatic organisms, contributing to improved management practices.

Support tools for decision making

It is important for decision-makers in the aquaculture industry to have access to accurate and reliable information to inform their decision-making processes. Several studies have explored different aspects of support tools for decision making in aquaculture (Bostock et al., 2010; G. Kumar et al., 2018).

The use of seasonal forecasting for decision support in marine fisheries and aquaculture, highlighting the potential benefits of incorporating seasonal forecasts into decision-making processes (Hobday et al., 2016).

Although not a current application in aquaculture, the example of the use the use of sensors in supporting health management on dairy farms can provide insights into the potential use of sensors in aquaculture decision-making (Rutten et al., 2013).

The use of geospatial assessment for site suitability in aquaculture can provide insights into decision-making processes related to site selection (Njoku et al., 2022).

The importance of accurate and actionable information for decision-making plays an important role in the farmers' response to weather and water-related stresses and manage climate risks (Hossain et al., 2021; U. Kumar et al., 2020).

Cloud computing is a service that provides computer system resources, with a particular focus on data storage (cloud storage) and computing power, accessible on-demand without the need for direct user management. In many cases, extensive networks of data centers, known as "large clouds," are spread across multiple locations. This infrastructure leverages resource sharing to ensure seamless operations and usually operates on a pay-as-you-go billing model. While this approach can minimize upfront capital costs, users should be mindful of potential unforeseen operating expenses.

The integration of cloud computing, the Internet of Things (IoT), and artificial intelligence (AI) techniques, collectively known as CIA, holds great potential for sustainable aquaculture development. The use of intelligent sensors, camera systems, and automated or remotely controlled monitoring/feeding strategies can reduce labor intensity, improve farming operations, and enhance food security in the aquaculture sector (Mustapha et al., 2021).

One relevant reference is the paper by Lecun et al. LeCun et al. (2015), which discusses deep learning, a subfield of machine learning that has shown remarkable success in image recognition tasks.

Deep learning algorithms, such as convolutional neural networks (CNNs), can be applied in aquaculture for fish detection and classification. These algorithms can analyze images or video footage captured by underwater cameras and automatically identify and track fish species, enabling efficient monitoring and management of aquaculture systems (C. Wang et al., 2021).

One example of cloud computing is the proposed smart aquaculture system based on the If This Then That (IFTTT) model and cloud integration. This system enables real-time monitoring and control of aquaculture operations, allowing farmers to remotely manage and optimize various parameters such as water quality, feeding schedules, and environmental conditions. The cloud integration aspect of the system ensures that data is securely stored and accessible from anywhere, facilitating efficient data analysis and decision-making (Dzulqornain et al., 2018).

Cloud computing also plays a significant role in data processing and analysis in aquaculture. With the ability to handle large volumes of data, cloud-based solutions enable advanced analytics, machine learning, and predictive modeling. This can help optimize feeding strategies, predict disease outbreaks, and improve overall farm productivity (Low et al., 2011).

AquaCloud, established in 2017, represents a significant big data initiative rooted in the aquaculture industry's quest to address common challenges and foster sustainable growth. This project is affiliated with NCE Seafood Innovation and was initially launched in collaboration with prominent cluster members, including Lerøy Seafood Group ASA, Grieg Seafood ASA, Mowi ASA, Bremnes Seashore AS, Lingalaks AS, Eide Fjordbruk, and Bolaks AS. Over the years, AquaCloud has witnessed substantial development, expanding its reach to encompass an even broader spectrum of leading aquaculture companies (AquaCloud, 2023).

Initially, this pioneering endeavor aimed to create a secure database for data storage and employ advanced analytics to pinpoint potential sea lice outbreaks. While this aspect of the project achieved some success, it faced challenges related to data quality and reliability, hindering the realization of its ambitious goals at the time (AquaCloud, 2023).

At the heart of AquaCloud lies the Data Platform, an ever-evolving repository of high-resolution data contributed by participating companies from their aquaculture operations. While respecting legal and competitive constraints, selected datasets are shared among participants and, in some cases, made available to third parties to fuel innovation (AquaCloud, 2023).

The project has evolved from being primarily a sea lice forecasting tool to serving as a central hub for industry activities, welcoming companies from various sectors within the aquaculture industry. In response to the initial findings of data quality deficiencies, the project initiated several workflows to address standardization needs across the industry (AquaCloud, 2023):

1. Sensor Data: An open IoT-based standard was introduced, facilitating equitable access to aquaculture sensors and systems.

2. Fish Health: Common standards were established for aspects such as identifying causes of mortality and categorizing fish groups, enabling seamless digital information exchange among health and welfare entities.

3. Environmental Data: A review of the environmental segment of the NS9417 standard aimed to enhance clarity and consistency in terminology and documentation methods for production-related environmental data.

The use of **Observers**, both linear, like Kalman filter, and nonlinear is very interesting for the future of aquaculture sector.

Kalman filter is a mathematical algorithm widely used in various fields, including aquaculture, to estimate the state of a dynamic system based on a series of noisy measurements.

The Kalman filter is a powerful tool for state estimation in linear systems. However, in nonlinear systems, the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) are commonly used to handle the nonlinearity. The EKF linearizes the system dynamics and measurement equations, while the UKF approximates the probability distribution of the state using a set of carefully chosen sigma points. These filters have been successfully applied in various fields, including control theory, battery monitoring, and electric vehicles (Afshar et al., 2019; Song et al., 2017; Wan & Van Der Menve, 2000).

In the context of aquaculture, the EKF and UKF can be utilized to estimate the state variables and parameters of nonlinear models used in aquafarm management. For example, by assimilating dissolved oxygen data, the EKF can provide dynamic estimations of oxygen demand, which can be used to optimize oxygen supply and improve the overall health and productivity of aquafarms.

By applying the Kalman filter in aquaculture, farmers and researchers can enhance the efficiency and sustainability of their operations. It enables them to make informed decisions based on accurate real-time data, leading to improved yields, reduced costs, and better environmental stewardship. The Kalman filter can be applied to monitor and control various aspects of fish farming, water quality, and environmental conditions: fish tracking and monitoring, water quality management, environmental parameter estimation, feed control, disease detection and prevention, stocking density management or water flow and circulation.

The continuous-discrete Kalman filter (CD-KF) has been used to assimilate dissolved oxygen data and obtain dynamic estimations of oxygen demand in land-based aquaculture farms. This approach can help optimize oxygen supply and improve the overall health and productivity of aquafarms (Royer & Pastres, 2023).

Decision support systems (DSS) play a crucial role in the aquaculture industry by providing valuable information and aiding in decision-making processes. Several studies have explored the use of various tools and techniques to support decision-making in aquaculture. One of the most important is the result of the Horizon 2020 project Co-creating a decision support framework to ensure sustainable fish production in Europe under climate change. They studied the implementing of a computer-based decision support system for the stakeholders in the context of climate change (Stavrakidis-Zachou et al., 2018).

Modern sensing Technique

Aquaculture has greatly benefited from modern sensing techniques. Remote sensing technology has been successfully applied in various aspects of aquaculture management and decision-making. Satellite remote sensing has been used to monitor and map coastal aquaculture areas, including coral reefs, wetlands, water quality, and fisheries. It provides continuous mapping capabilities in the coastal zone, making it more advantageous than optical remote sensing instruments. Remote sensing technology has also been used to extract marine aquaculture areas, although there are differences between marine and pond aquaculture. Additionally, remote sensing has enabled high-resolution mapping of pond aquaculture, supporting the sustainable development of coastal ecosystems (McCarthy et al., 2017; Ottinger et al., 2017, 2018; J. Wang et al., 2022).

Specifically, remote sensing has been used to monitor raft aquaculture products and to develop an improved method for extracting raft aquaculture areas from remote sensing images, highlighting the relevance of remote sensing in aquaculture monitoring, improving the accuracy and periodic monitoring capabilities of remote sensing in aquaculture management, particularly in mapping coastal aquaculture areas using object-based image analysis (Cui et al., 2019; Fu et al., 2019).

DeepSense is a world class big ocean data innovation environment that helps drive growth in the ocean economy with collaborative academic industry research (DeepSense, 2023)

There are some examples of the use of **satellite observation** for different uses in aquaculture, both for fish and molluscs, such as site selection and marine spatial planning, remote sensing or estimation of aquaculture production (Kang et al., 2019; Ottinger et al., 2017, 2018; Snyder et al., 2017; J. Wang et al., 2022).

Underwater wireless acoustic sensors are designed to operate in the challenging underwater environment and provide real-time data for decision-making and management.

In terms of aquaculture water quality monitoring, a comprehensive review discusses the sensors, biosensors, and analytical technologies available for this purpose. These technologies enable the continuous monitoring of parameters such as temperature, dissolved oxygen, pH, and nutrient levels, ensuring optimal conditions for aquaculture operations (Su et al., 2020).

Underwater acoustic modems are essential components of underwater wireless sensor networks. These modems facilitate reliable communication between the sensors deployed in the water and the data collection and management systems. They are designed to withstand the harsh underwater conditions and provide efficient data transmission (Sendra et al., 2016).

Single beam sonar is an acoustic sensing technique with a high potential use in aquaculture for various purposes, including fish detection, biomass estimation, and habitat mapping. Some studies have used single beam sonar for other purposes that can be very useful in future for aquaculture farms. This study suggests that single beam sonar systems can be utilized to actively detect and select targets of interest in aquaculture farms. By adjusting the sonar beam direction and angle, farmers should be able to effectively scan the aquatic environment and gather information on fish presence, behavior, and habitat characteristics. This information can aid in making informed decisions regarding feeding, stocking, and overall management of aquaculture operations. While further research specific to the use of single beam sonar in aquaculture is needed, the findings from the study on echolocating porpoises provide a foundation for understanding the potential applications and benefits of this acoustic sensing technique in the aquaculture industry (Wisniewska et al., 2012).

Hydroacoustic sensing and telemetry have emerged as important tools in aquaculture for monitoring various aspects of fish behavior, welfare, and production. Telemetry, which involves the use of physiological telemetry devices, has been used to remotely monitor fish activity and energetics. This technology has proven valuable in assessing the swimming activity and energetic expenditure of fish in both controlled conditions and natural environments. Hydroacoustic sensing utilizes sound waves to assess fish biomass, spatial distribution, and behavior. It has been successfully applied in aquaculture ponds to estimate the standing stock of fish species such as Nile tilapia. Additionally, hydroacoustic techniques have been used to estimate the biomass and spatial distribution of fish in sea cages and coastal waters, with acoustic target strength being a crucial parameter in this method (Cooke et al., 2000; Cooke et al., 2004; Kim et al., 2018; J. M. Liu et al., 2022).

The integration of hydroacoustic sensing and telemetry in aquaculture has provided valuable insights into fish behavior and welfare. For example, these technologies have been used to monitor feeding behavior in fish aquaculture, with acoustics, computer vision, and telemetry being the main approaches employed. Telemetry-based systems have also been developed to monitor the feeding behavior of Atlantic salmon in aquaculture sea-cages. Furthermore, telemetry has been used to study the reaction of fish to stress factors, such as oxygen deficiency, in pond aquaculture. These studies highlight the potential of telemetry in assessing fish responses to various environmental conditions and stressors (Bauer & Schlott, 2006; Darodes de Tailly et al., 2021; Føre et al., 2011).

In addition to fish behavior and welfare, hydroacoustic sensing and telemetry have been utilized for monitoring aquaculture production and environmental factors. Remote sensing, including hydroacoustic methods, has been employed to estimate aquaculture production based on Earth observation data. This approach takes advantage of the fact that active aquaculture ponds are permanently water-covered year-round, making them suitable for remote sensing applications. Furthermore, hydroacoustic data collected by sensors have been used to gain insights into fish behavior and inform precision aquaculture practices (O'Donncha et al., 2021; Ottinger et al., 2018).

Blockchain technology

Blockchain technology has the potential to revolutionize the aquaculture sector by addressing various challenges and improving efficiency. The use of blockchain in aquaculture can enhance traceability, improve supply chain management, and promote sustainability. By implementing blockchain technology, the aquaculture industry can ensure transparency and accountability throughout the supply chain, from farm to fork. Blockchain can provide a decentralized and immutable ledger that records every transaction and movement of seafood products, enabling consumers to verify the origin and quality of the products (Feng et al., 2020; Mileti et al., 2023; Tolentino-Zondervan et al., 2023).

One of the key benefits of blockchain technology in aquaculture is improved traceability. Blockchain can enable the tracking of seafood products from their source to the consumer, ensuring that the products are safe, sustainable, and comply with regulations (Mileti et al., 2023; Tolentino-Zondervan et al., 2023). Additionally, blockchain can facilitate the integration of different stakeholders in the supply chain, such as farmers, processors, distributors, and retailers, by providing a shared platform for data exchange and collaboration (Tolentino-Zondervan et al., 2023).

Furthermore, blockchain technology can enhance the efficiency of aquaculture production. By utilizing digital technologies such as the Internet of Things, big data, and artificial intelligence, blockchain can enable real-time monitoring and data collection, leading to optimized production processes and resource management. For example, sensors can be used to monitor water quality, feeding patterns, and fish health, allowing farmers to make data-driven decisions and prevent disease outbreaks (Zhang & Gui, 2023).

The adoption of blockchain technology in aquaculture is not without challenges. Implementation difficulties, particularly for small and medium-sized enterprises, and the need for standardized protocols and interoperability are some of the obstacles that need to be overcome. Additionally, the integration of blockchain into existing systems and the establishment of trust among stakeholders may require time and resources (Alimohammadlou & Alinejad, 2023; Feng et al., 2020).

2.2.1.5. Conclusions

Summarising, there are many different technologies that can be used in aquaculture farms to improve them to precision farms. Those technologies have the following advantages:

- The applications of IoT in aquaculture farms include water quality monitoring, fish monitoring, farm monitoring and management, and precision aquaculture. These applications leverage IoT technology to collect real-time data, enable remote monitoring and control, and support data-driven decision-making in aquaculture operations.
    - GSM technology.
    - On-site and remote interface.
    - Water quality sensors.
    - Fish behavior sensors.
    - Early warning monitoring.
- Robotics can play a vital role in aquaculture by enabling advancements in fish locomotion research, sensor payload development, underwater object detection, water quality

monitoring, and automation. The integration of robotics in aquaculture systems offers numerous benefits, including improved efficiency, productivity, and sustainability.

    - Remote controlled or autonomous vehicles (ROV/AUV).
- Cameras have proven to be valuable tools in aquaculture, contributing to fish welfare monitoring, water quality assessment, and spatial mapping of aquaculture facilities. The integration of cameras with other technologies, such as UAVs and remote sensing, enhances the efficiency and accuracy of data collection and analysis in aquaculture operations.
    - Surface camera.
    - Submerged cameras (Feeding camera, stereo camera).
    - Image processing techniques (Hyperspectral or multispectral imager, 3d analyser).
    - Computer vision and machine learning techniques.
    - Image processing techniques.
- Support tools for decision making are tools that can play a support tool in aquaculture as it's a multidimensional process that requires access to accurate and reliable information. The references cited in this response provide valuable insights into different aspects of decision support in aquaculture and can inform decision-making processes in the industry.
    - Cloud computing.
    - AquaCloud (predicts sea-lice outbreaks)
    - Observers (Kalman filtering, nonlinear observers).
    - Decision Support Systems (DSS).
- Modern sensing techniques
    - DeepSense (Big Ocean data innovation environment).
    - Satellite observation combined (or not) with sensor and/or in situ observation.
    - Underwater wireless acoustic sensors.
    - Single beam sonar.
    - Hydroacoustic sensing and telemetry (active and passive).
- Blockchain technology holds great promise for the aquaculture sector. It can improve traceability, enhance supply chain management, and promote sustainability. By leveraging digital technologies and ensuring transparency, blockchain can revolutionize the way seafood products are produced, distributed, and consumed. However, challenges related to implementation and standardization need to be addressed for the widespread adoption of blockchain in aquaculture.

2.2.2.Data collection from stakeholders

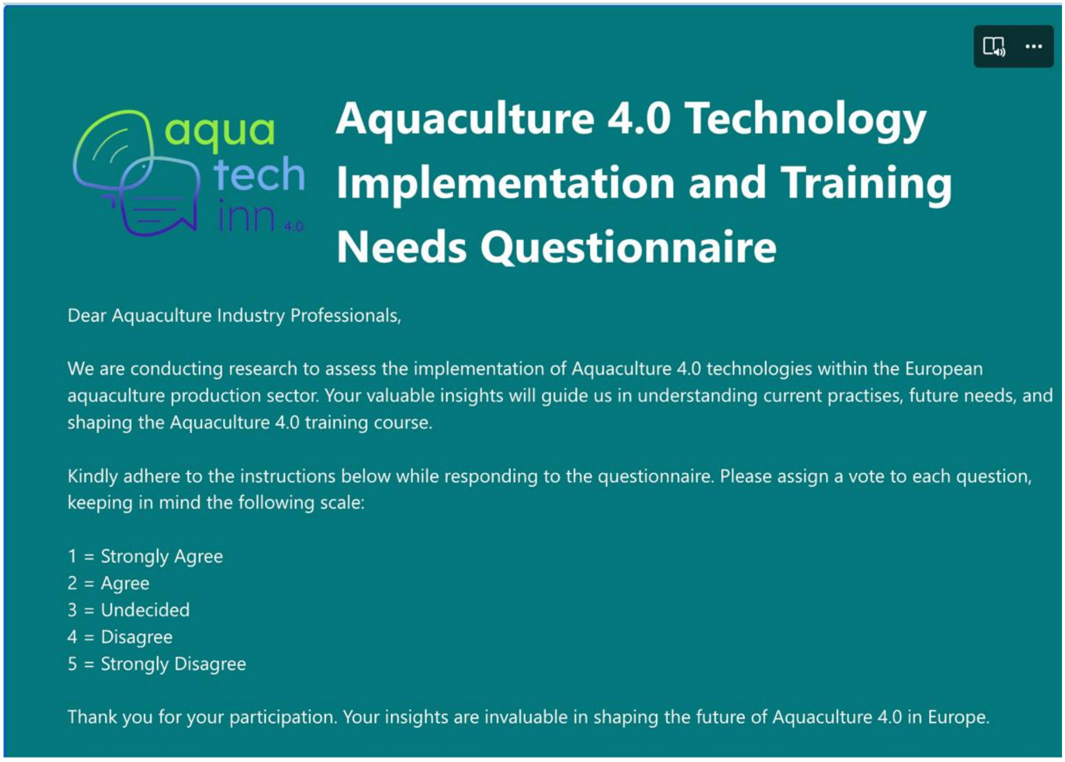
2.2.2.1. Survey preparation

The working group discussed the results of the scientific review and prepared a survey to be distributed to producers in the different countries.

In order to maximise the number of responses, the survey was designed to be simple and possible to be answered in a short time. It was divided into different blocks:

- Questions about the characteristics of the farm: Country, species, type of farm and environment.
- Questions about the implementation of the different technologies identified during the scientific review: Internet of Things, Robotics, Camera systems, Support tools for decision making, Modern sensing techniques, Blockchain technology. In this block, the farmers had to answer with the following scale:
    - 1 = Strongly Agree
    - 2 = Agree
    - 3 = Undecided
    - 4 = Disagree
    - 5 = Strongly Disagree
- Open question about the top priorities for the course structure and needs.
- Open question about the key needs for the Vocational Training and Curriculum development in the aquaculture industry.

The survey was prepared in English and translated into the different languages of the consortium partners (Italian, French, Spanish, Turkish, Portuguese and Greek).



Aquaculture 4.0 Technology Implementation and Training Needs Questionnaire

Dear Aquaculture Industry Professionals,

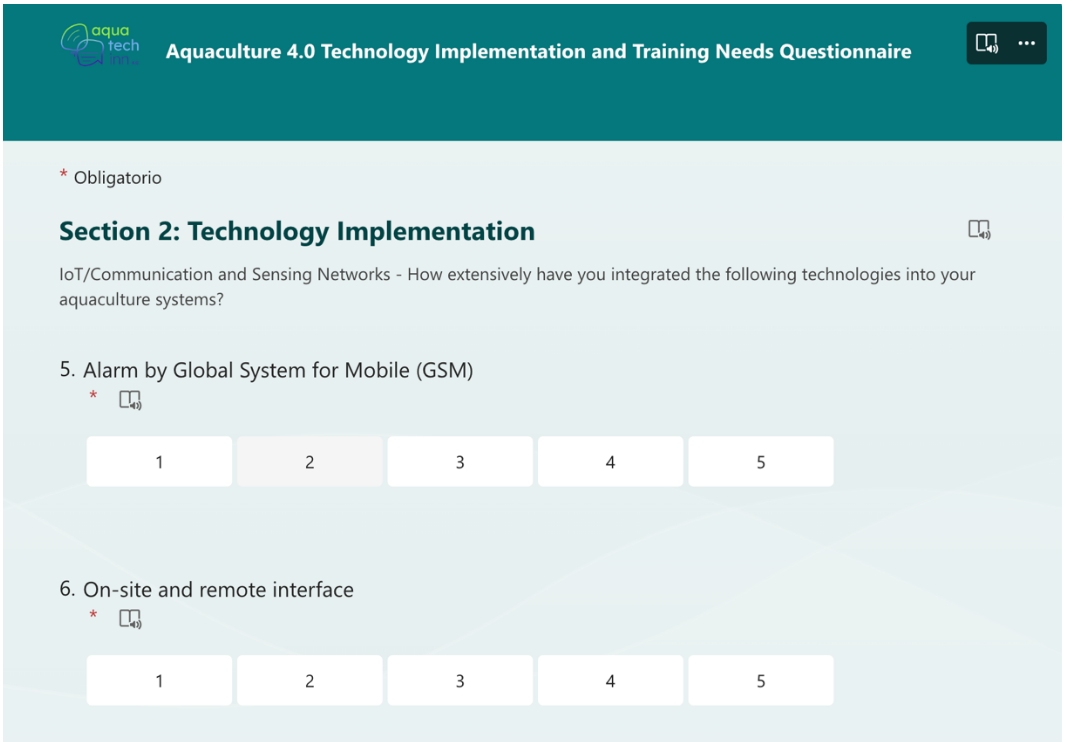
We are conducting research to assess the implementation of Aquaculture 4.0 technologies within the European aquaculture production sector. Your valuable insights will guide us in understanding current practises, future needs, and shaping the Aquaculture 4.0 training course.

Kindly adhere to the instructions below while responding to the questionnaire. Please assign a vote to each question, keeping in mind the following scale:

1 = Strongly Agree
2 = Agree
3 = Undecided
4 = Disagree
5 = Strongly Disagree

Thank you for your participation. Your insights are invaluable in shaping the future of Aquaculture 4.0 in Europe.

Illustration 1. Screenshot of the header of the questionnaire.



Aquaculture 4.0 Technology Implementation and Training Needs Questionnaire

* Obligatorio

Section 2: Technology Implementation

IoT/Communication and Sensing Networks - How extensively have you integrated the following technologies into your aquaculture systems?

5. Alarm by Global System for Mobile (GSM) *

1	2	3	4	5

6. On-site and remote interface *

1	2	3	4	5

Illustration 2. Screenshot of beginning of Section 2 of the questionnaire.

2.2.2.2. Survey content

The survey was divided into different sections as follow.

Section 1: Species.

Species and Farm Characteristics.

1a. Where are you located?

☐ France	☐ Greece	☐ Italy
☐ Portugal	☐ Spain	☐ Turkey
☐ Other		

1b. Species: Please specify the species you primarily focus on

☐ Sea bass	☐ Sea bream	☐ Meagre
☐ Rainbow trout	☐ Carp	☐ Eel
☐ Tuna	☐ Turbot	☐ Sole
☐ Mussels	☐ Oysters	☐ Clams
☐ Other		

1c. Type of farm: What type of farm do you operate?

☐ RAS

☐ Sea cages

☐ Open system (raceways, flow-through tanks, ponds...)

☐ Molluscs on the bottom

☐ Molluscs on suspension (Longlines, raft, batea…)

☐ Raised molluscs (in a container or tables with bags)

☐ Other

1d. Environment: Specify the environment of your farm.

☐ Marine

☐ Freshwater

☐ Brackish

Section 2: Technology Implementation.

IoT/Communication and Sensing Networks - How extensively have you integrated the following technologies into your aquaculture systems?

2a. Alarm by Global System for Mobile (GSM).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2b. On-site and remote interface.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2c. Water quality sensors (real-time, remote, online or automated monitoring).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2d. Fish behavior sensors.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

2e. Early warning monitoring.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 3: Robotics.

Are remote-controlled or autonomous vehicles (ROV/AUV) currently in use in your aquaculture practices?

3a. Remote controlled or autonomous vehicles (ROV/AUV).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 4: Camera Systems-based Applications and Solutions.

How extensively have you integrated Camera system-based applications and solutions into your aquaculture systems?

4a. Surface camera.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4b. Submerged cameras (Feeding camera, stereo camera).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4c. Image processing techniques (Hyperspectral or multispectral imager, 3d analyser)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4d. Computer vision and machine learning techniques.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

4e. Image processing techniques.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 5: Support Tools for Decision Making.

To what extent do you use support tools for decision making into your aquaculture systems?

5a. Cloud computing.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5b. AquaCloud (predicts sea-lice outbreaks)

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5c. Observers (Kalman filtering, nonlinear observers).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

5d. Decision Support Systems (DSS).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 6: Modern Sensing Technique.

To what extent do you use support tools for decision making into your aquaculture systems?

6a. DeepSense (Big ocean data innovation environment).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

6b. Satellite observation combined (or not) with sensor and/or in situ observation.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

6c. Underwater wireless acoustic sensors.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

6d. Single beam sonar.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

6e. Hydroacoustic sensing and telemetry (active and passive).

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 7: Blockchain Technology.

To what extent do you use or implement blockchain technology in your aquaculture processes?

7a. Blockchain Technology.

☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5

Section 8: Training Course Structure and Needs

8a. What do you consider the top priorities for training courses in Aquaculture 4.0?

Section 9: Vocational Training and Curriculum Development

9a. What are the key needs for vocational training in the aquaculture industry?

2.2.2.3. Survey distribution

The survey was distributed to the associated farmers from the Bussiness associations participating in the consortium. It was also sent to the farmers from other countries present in the Stakeholders database (Deriverable D10.1. Database of Stakeholders and Beneficiaries (DSB)).

2.2.2.4. Survey results

A total of 69 responses to the questionnaire were received. Some of the answers cover more than one farm, as there are many companies that have many sites with different species and environments.

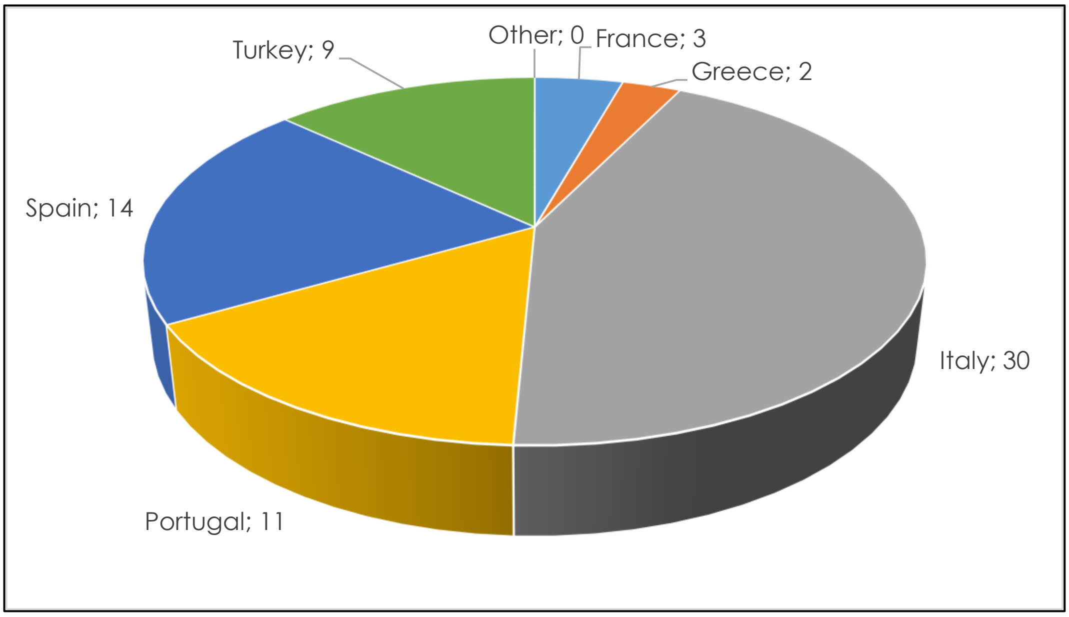


Figure 1. Distribution of responses by country.

Even though the survey was delivered to farmers from the list of stakeholders, which includes farms from many countries around Europe and the participants countries, the number of responses was bigger in those countries where a partner of the consortium of the AquaTechInn 4.0 projec is a Business Association, as they are able to reach directly the farmers.

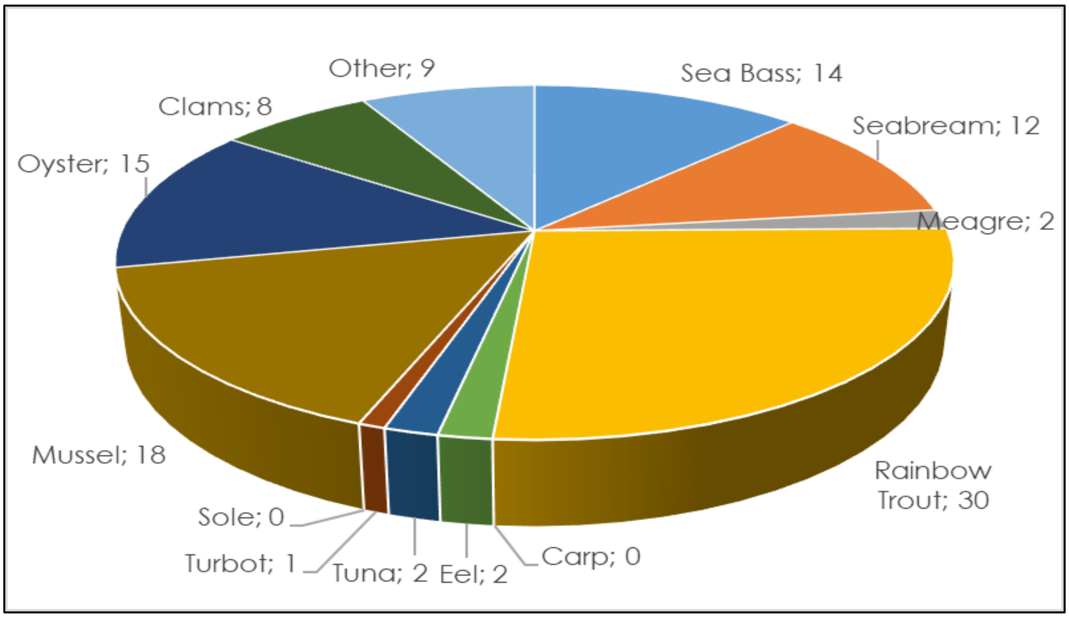


Figure 2. Species produced on the farms that responded to the questionnaire.

More than 10 species are farmed produced at the farms that responded to the questionnaire, since 9 farms indicate that they produce "other" species. There is a good distribution of the species, as its covered the main species produced at the Mediterranean aquaculture.

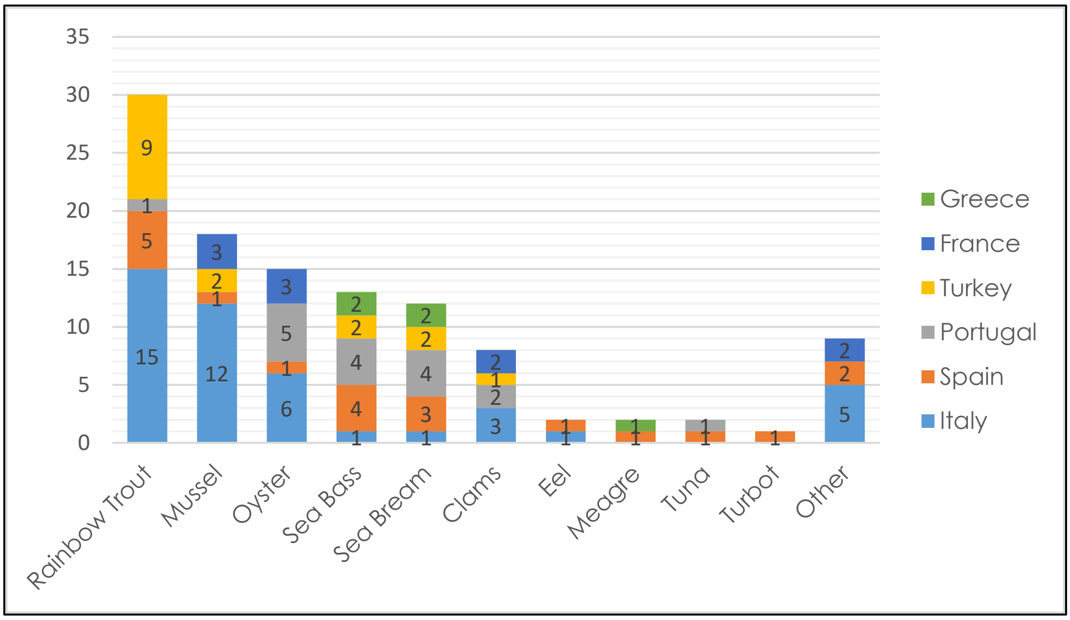


Figure 3. Distribution by species and countries of the responses to the questionnaire.

Rainbow Trout, followed by mussels, oysters, Sea Bass and Sea Bream, are the most represented species. This are the species with the highest production in the countries participating in this project.

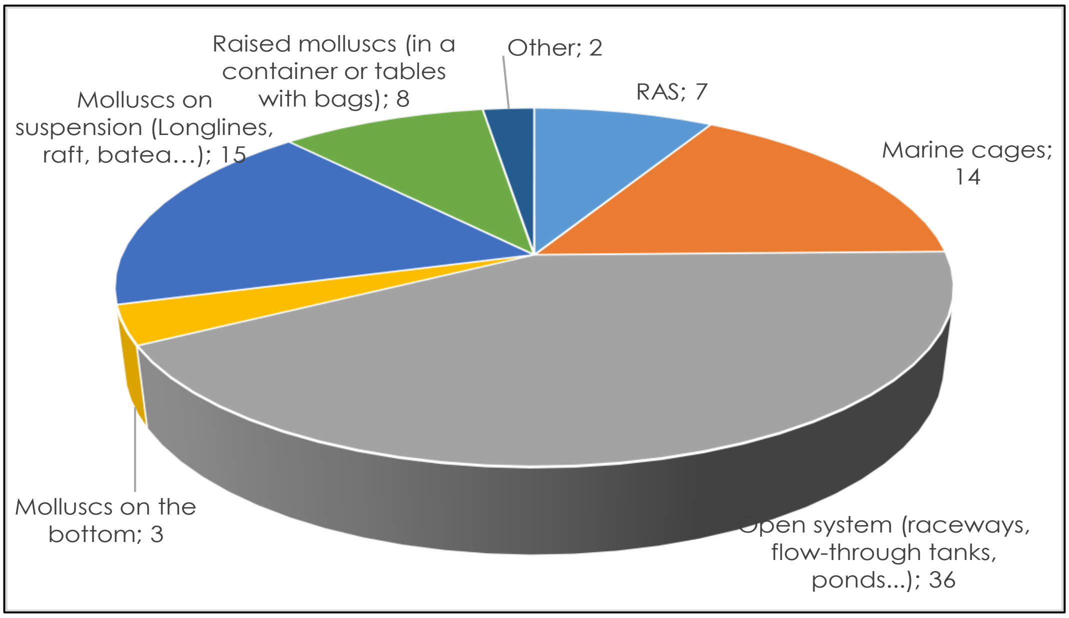


Figure 4. Production system of the farms that responded to the questionnaire.

As showed in the previous figure, the distribution of the farms covers all the different types of aquaculture production systems. The highest percentage belongs to aquaculture open systems. This could be explained by the fact that this system can be used in marine, brackish and freshwater to produce different species of fish, being one of the most extended systems in Europe.

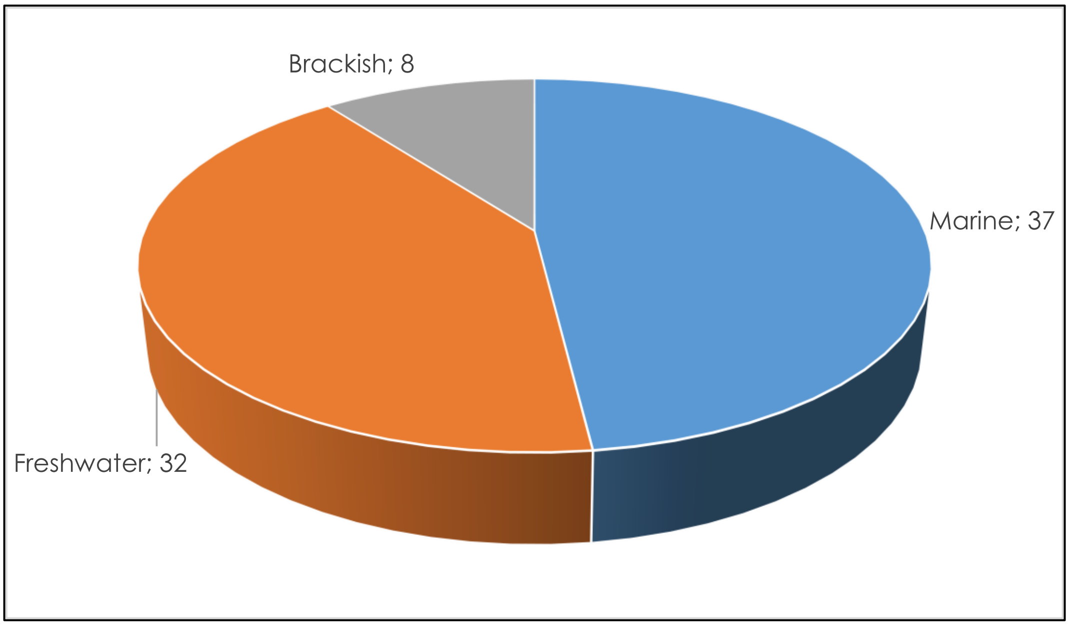


Figure 5. Environment of the farm that responded to the questionnaire.

The distribution of the environment origin is also well balanced between freshwater and marine farms. Brackish environment is less common, and it's well represented in the answers received.

Table 2. Distribution of the answers to each question. Included the percentage for each question.

	1	2	3	4	5
2a	29 42.0 %	7 10.1 %	7 10.1 %	9 13.0 %	17 24.6 %
2b	26 37.7 %	10 14.5 %	8 11.6 %	5 7.2 %	20 29.0 %
2c	24 34.8 %	11 15.9 %	10 14.5 %	6 8.7 %	18 26.1 %
2d	24 34.8 %	5 7.2 %	5 7.2 %	6 8.7 %	29 42.0 %
2e	20 29.0 %	13 18.8 %	9 13.0 %	4 5.8 %	23 33.3 %
3a	25 36.2 %	4 5.8 %	10 14.5 %	5 7.2 %	25 36.2 %
4a	28 40.6 %	7 10.1 %	10 14.5 %	3 4.3 %	21 30.4 %
4b	27 39.1 %	0 0.0 %	7 10.1 %	4 5.8 %	31 44.9 %
4c	26 37.7 %	2 2.9 %	6 8.7 %	3 4.3 %	32 46.4 %
4d	25 36.2 %	2 2.9 %	6 8.7 %	2 2.9 %	34 49.3 %
4e	25 36.2 %	5 7.2 %	5 7.2 %	2 2.9 %	32 46.4 %
5a	19 27.5 %	10 14.5 %	8 11.6 %	9 13.0 %	23 33.3 %
5b	25 36.2 %	3 4.3 %	3 4.3 %	2 2.9 %	36 52.2 %
5c	25 36.2 %	2 2.9 %	5 7.2 %	3 4.3 %	34 49.3 %
5d	24 34.8 %	3 4.3 %	8 11.6 %	4 5.8 %	30 43.5 %
6a	27 39.1 %	1 1.4 %	4 5.8 %	2 2.9 %	35 50.7 %
6b	20 29.0 %	2 2.9 %	6 8.7 %	1 1.4 %	40 58.0 %
6c	28 40.6 %	1 1.4 %	3 4.3 %	1 1.4 %	36 52.2 %
6d	25 36.2 %	0 0.0 %	7 10.1 %	1 1.4 %	36 52.2 %
6e	27 39.1 %	1 1.4 %	4 5.8 %	2 2.9 %	35 50.7 %
7a	27 39.1 %	5 7.2 %	6 8.7 %	7 10.1 %	24 34.8 %

In the Table 2, the distribution of the answers to each question is showed. The shaded cells are the most vote in each category.

As can be seen from these results, many of the selected technologies are of high interest to companies in the sector.

There are also many technologies that are not implemented at the farm level, but this hasn't mean that it's not interesting for them. Some of these technologies are already being applied in some farms, and others have a high potentiality to help the sector to achieve the goal to transform into the Aquaculture 4.0, the aquaculture of the future.

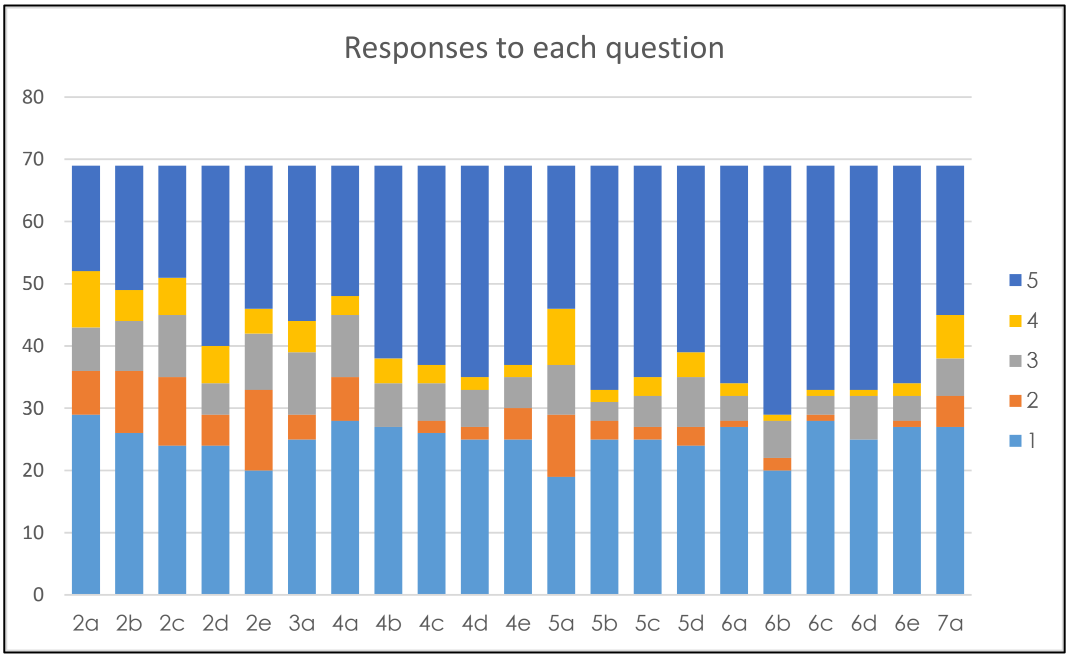
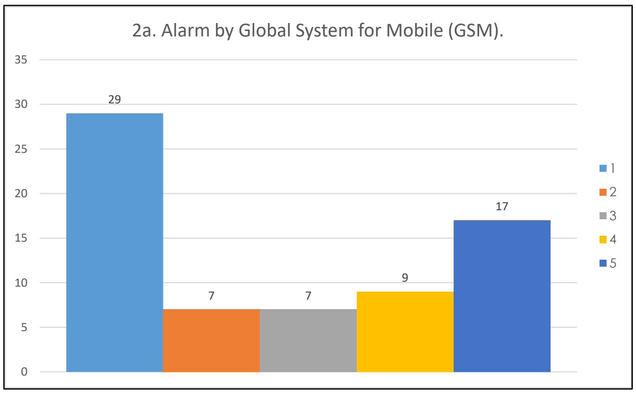


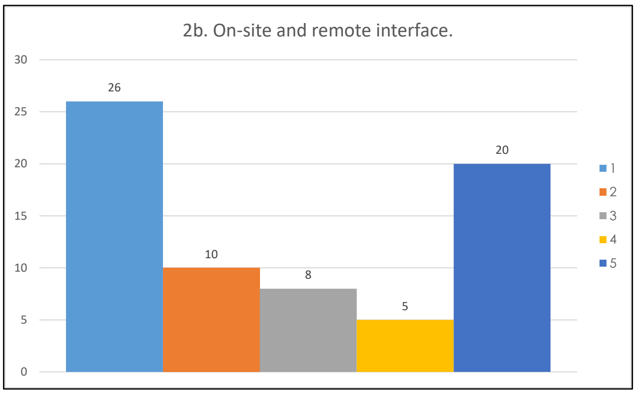
Figure 6. Distribution of the answers to each question.

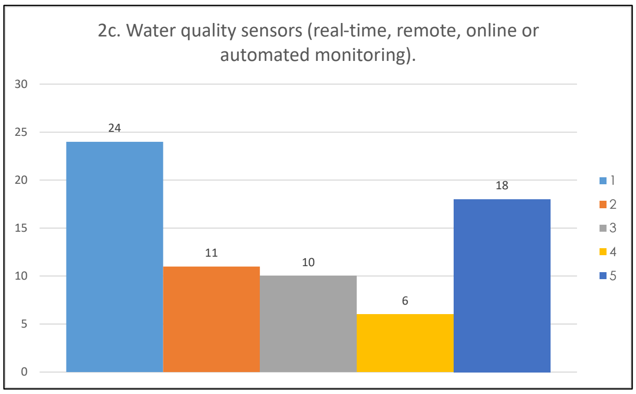
Some very specific technologies are not interesting to all the companies of the aquaculture sector. For example, AquaCloud technology can be used to predict the appearance of sea lice (or other kind of similar pathogens), and this can be not so interesting to some specific producers.

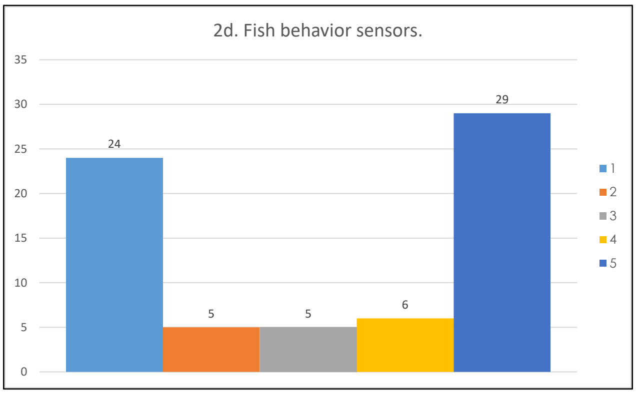
The results of the survey stress the necessity of improving the training of the personnel of the aquaculture farms and the programs of the Vocational Training, including those new technologies that can be so useful for the future of the aquaculture sector.

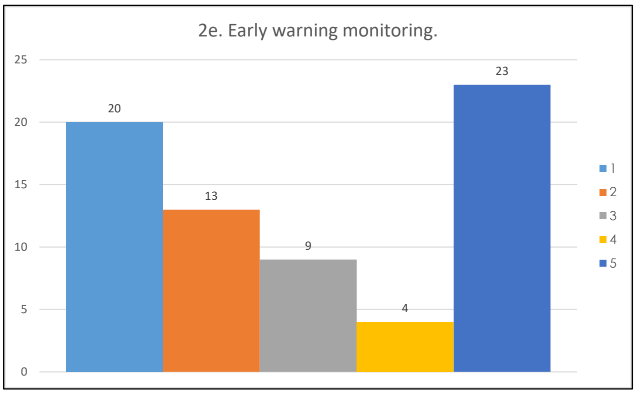
In the following charts, the response to each question is showed.

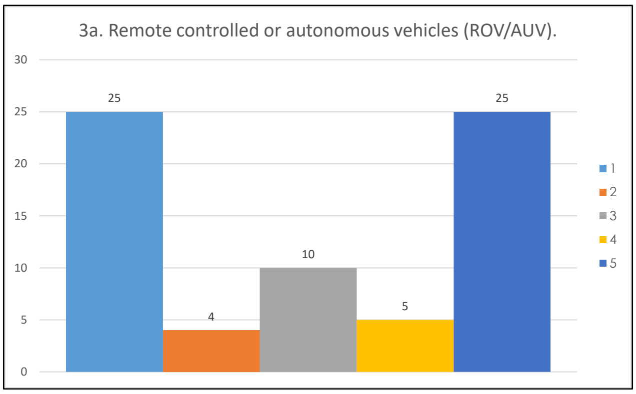


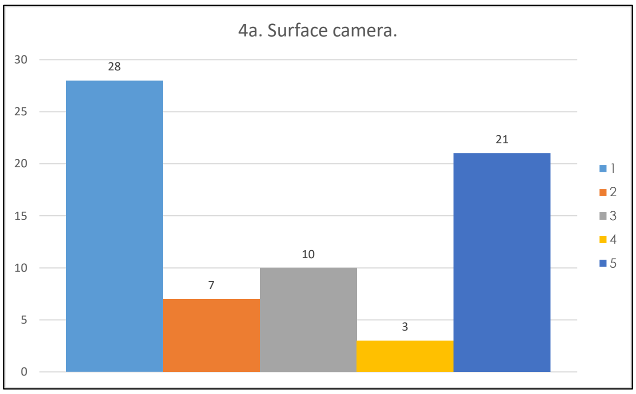


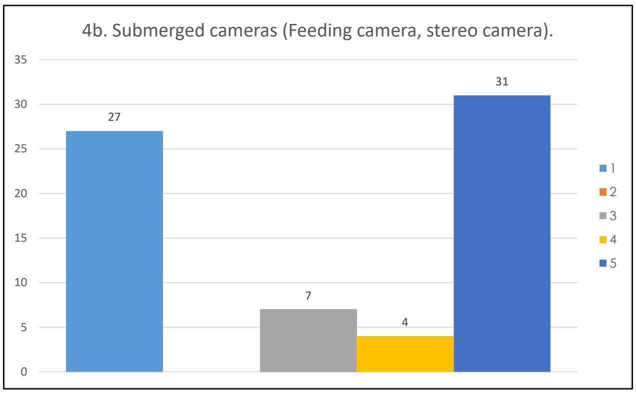


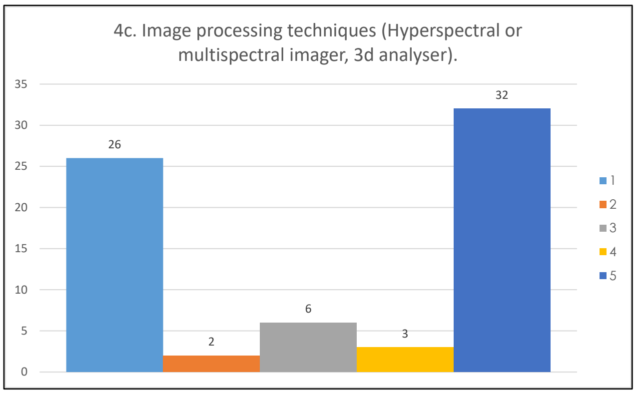











4c. Image processing techniques (Hyperspectral or multispectral imager, 3d analyser).
0 5 10 15 20 25 30 35
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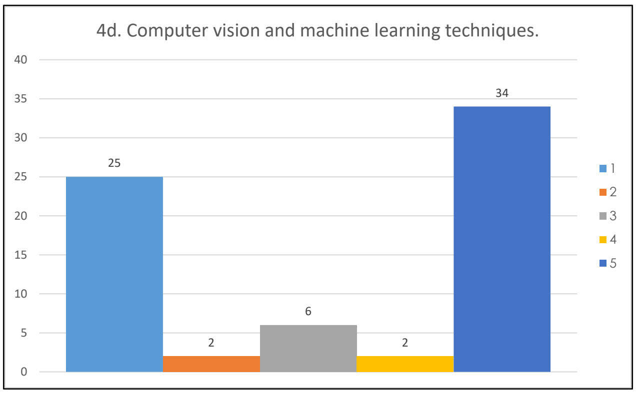
4d. Computer vision and machine learning techniques.
0 5 10 15 20 25 30 35 40
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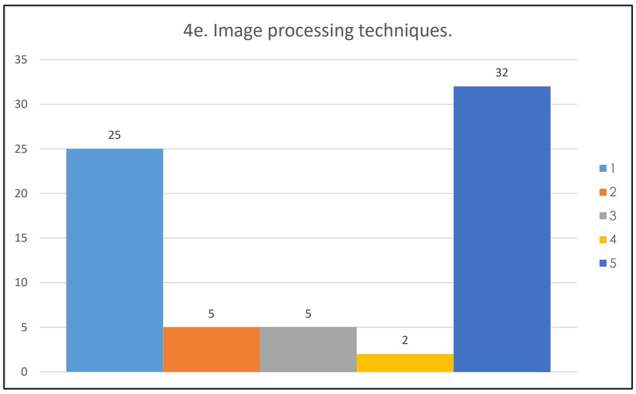
4e. Image processing techniques.
0 5 10 15 20 25 30 35
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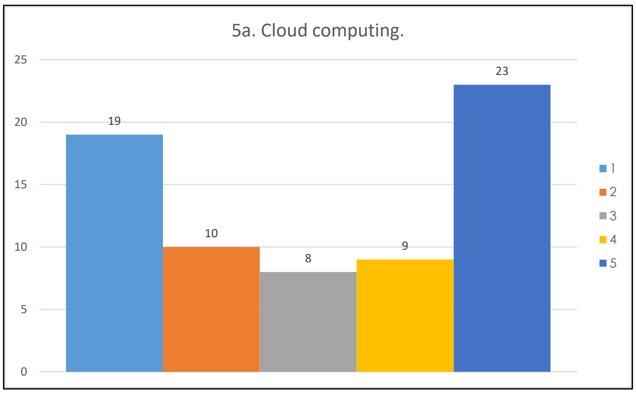
5a. Cloud computing.
0 5 10 15 20 25
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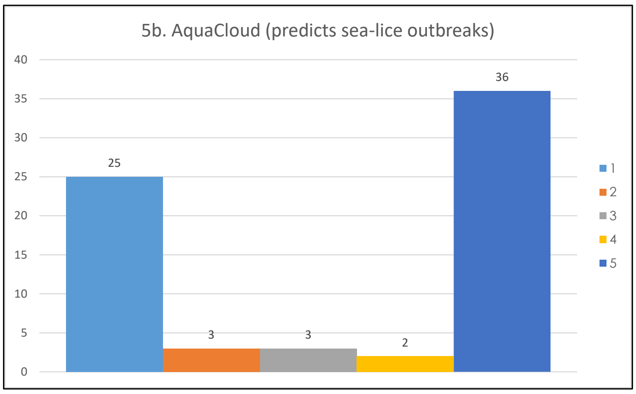
5b. AquaCloud (predicts sea-lice outbreaks)
0 5 10 15 20 25 30 35 40
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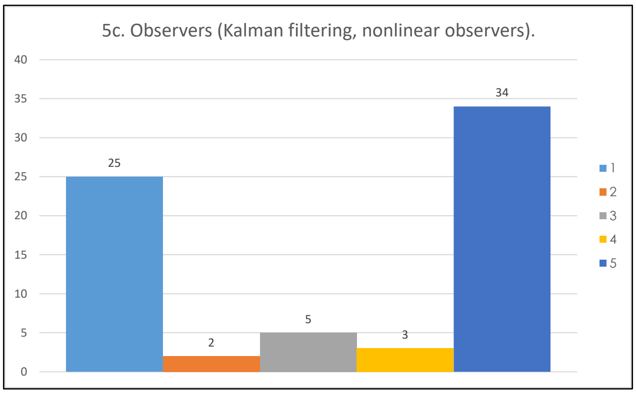
5c. Observers (Kalman filtering, nonlinear observers).
0 5 10 15 20 25 30 35 40
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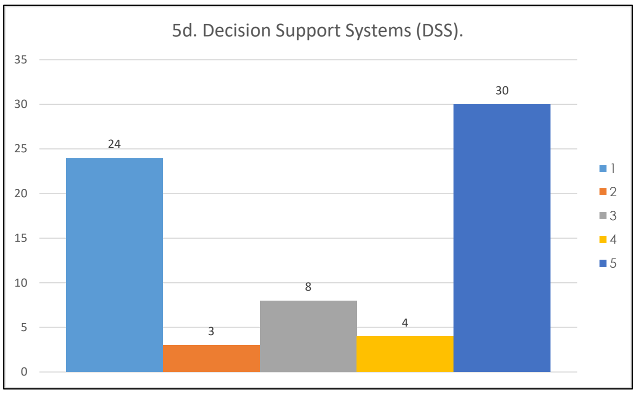
5d. Decision Support Systems (DSS).
0 5 10 15 20 25 30 35
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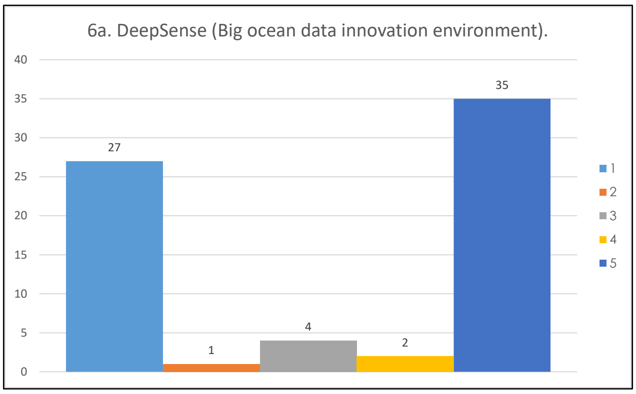
6a. DeepSense (Big ocean data innovation environment).
0 5 10 15 20 25 30 35 40
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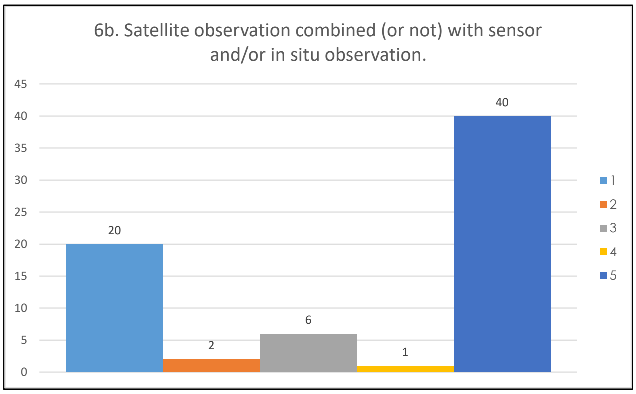
6b. Satellite observation combined (or not) with sensor and/or in situ observation.
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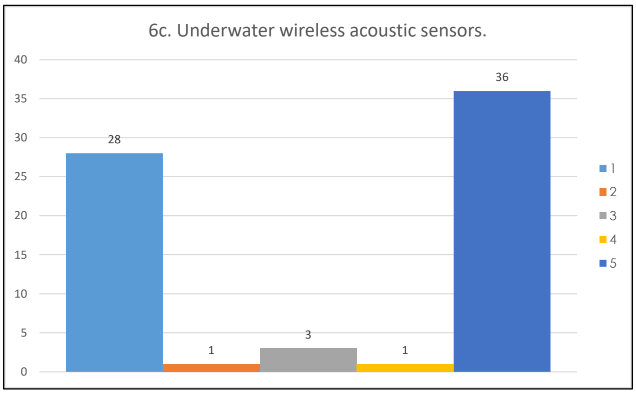
6c. Underwater wireless acoustic sensors.
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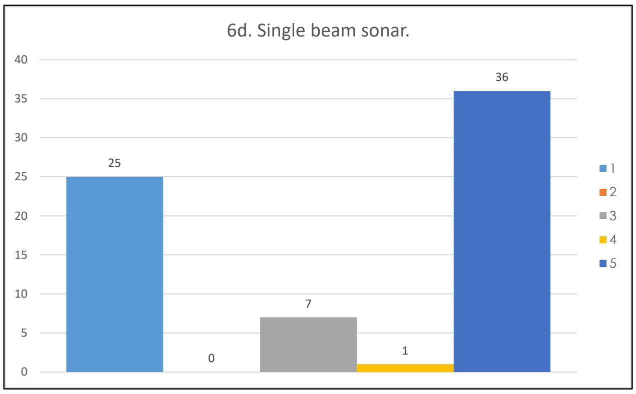
6d. Single beam sonar.
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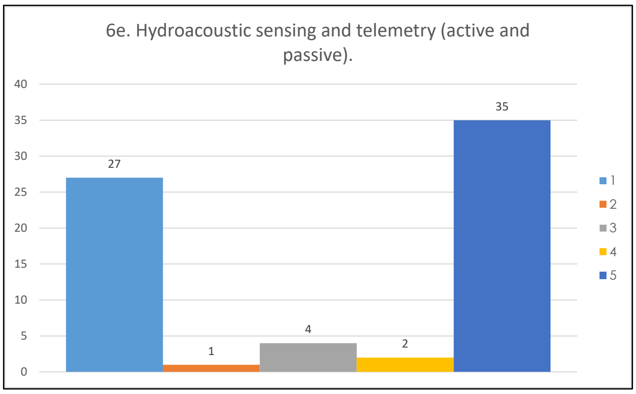
6e. Hydroacoustic sensing and telemetry (active and passive).
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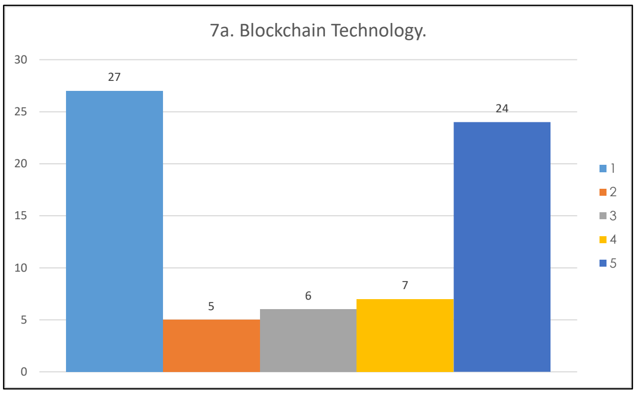
7a. Blockchain Technology.
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The last part of the questionnaire was to ask the farmers two open answer questions:

- What do you consider the top priorities for training courses in Aquaculture 4.0?
- What are the key needs for vocational training in the aquaculture industry?

Some of the most relevant answers emphasise different very interesting issues:

What do you consider the top priorities for training courses in Aquaculture 4.0?

- Acquiring skills to identify the suitability of breeding sites.
- Process automation, , including automated feeding and control of the water quality.
- Monitoring animal health and welfare on the farm. Also preventing the appearance of diseases or minimizing its impact.
- Remote monitoring and control of the farm.
- Use of new technologies to improve the farm management.
- Improve the adaptation of the business world and its workers to new technologies and advances in the field, in order to industrialise the sector and automate processes.
- Improving working conditions / employee health.
- The priority would be short-term (prevention of extreme events) and long-term (historical data analysis) monitoring of key environmental parameters (temperature, chlorophyll and turbidity).
- Increase the use of domestic technology and resources in aquaculture production,
- Possibility to examine of R&D in Aquaculture.
- Training is useful in every work and process related to aquaculture, especially in fish health and fattening.
- Use of advanced equipment and high-tech tools.
- Routine farming activities.

What are the key needs for vocational training in the aquaculture industry?

- Being prepared for the challenges related with climate change.
- Importance of the technological development.
- Application of new technologies to control and ensure Animal Welfare.
- Biosecurity, Animal Welfare, Applied Aquaculture Technologies training courses.
- Early recognition of fish diseases.
- Training of polyvalent operators, capable of dealing with integrated breeding with new technologies.
- More than training courses related with the opportunities of the new technologies.
- Techniques and technologies, good practice and safety.

- Improve the knowledge in farm management.
- Use of robotic devices and control software for fish farmers.

2.3. Conclusions / Next steps

Aquaculture 4.0 can help the European sector to adapt to the future challenges, such as climate change, new species, improve the profitability in a more competitive context. Animal welfare is also one of the most important challenges for the sector, and the new technologies can help to improve it. Animal health has a direct impact on Food Safety and Public Health. New technologies can help the farmers to upgrade the health management, and to be prepared for the future.

After performing the scientific review, some technologies have been selected because of their potential application in aquaculture:

- Internet of Things (IoT).
  - GSM technology.
  - On-site and remote interface.
  - Water quality sensors.
  - Fish behavior sensors.
  - Early warning monitoring.
- Robotics.
  - Remote controlled or autonomous vehicles (ROV/AUV).
- Cameras.
  - Surface camera.
  - Submerged cameras (Feeding camera, stereo camera).
  - Image processing techniques (Hyperspectral or multispectral imager, 3d analyser).
  - Computer vision and machine learning techniques.
  - Image processing techniques.
- Support tools for decision making.
  - Cloud computing.
  - AquaCloud (predicts sea-lice outbreaks)
  - Observers (Kalman filtering, nonlinear observers).
  - Decision Support Systems (DSS).
- Modern sensing techniques
  - DeepSense (Big ocean data innovation environment).
  - Satellite observation combined (or not) with sensor and/or in situ observation.
  - Underwater wireless acoustic sensors.
  - Single beam sonar.
  - Hydroacoustic sensing and telemetry (active and passive).
- Blockchain technology.

These results have to be studied and adapted for future tasks, selecting those technologies more interesting for the farmers.

It can also be interesting to adapt the contents depending on the species or type of facility, focusing on the most interesting for each one.

It will be highly interesting to study the comments done by the farmers in the survey to adapt the future contents of the training courses for Vocational Training to their needs.

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4. Appendices

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4.2. Survey results

ID	Country	Species	Type of Farm	Environment	2a	2b	2c	2d	2e	3a	4a	4b	4c	4d	4e	5a	5b	5c	5d	6a	6b	6c	6d	6e	7a
1	France	Mussels;Oysters; Other	Open system (raceways, flow-through tanks, ponds...)	Marine;	4	1	3	1	2	1	1	1	1	1	1	2	1	1	1	1		1	1	1	1
2	France	Mussels; Oysters; Clams	Molluscs on the bottom; Molluscs on suspension (Longlines, raft, batea…); Raised molluscs (in a container or tables with bags)	Marine;	2	5	2	5	2	3	5	5	5	5	4	4	5	5	5	5	3	5	5	5	4
3	France	Mussels; Oysters; Clams; Other	Molluscs on suspension (Longlines, raft, batea…); Molluscs on the bottom; Raised molluscs (in a container or tables with bags); Système ouvert;	Marine; Brackish;	3	5	4	5	5	4	5	5	5	5	5	5	5	5	5	5	5	5	5	4	5
4	Greece	Sea Bass; Sea Bream	Sea cages	Marine;	2	5	1	5	5	2	1	3	5	5	5	5	5	5	5	5	5	5	5	5	4
5	Greece	Sea Bass; Sea Bream; Meagre	Sea cages	Marine;	5	4	1	5	5	1	1	1	5	5	5	5	5	5	5	5	5	5	5	5	5
6	Italy	Mussels	Open system (raceways, flow-through tanks, ponds...)	Marine;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		1	1	1	1
7	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	2	4	2	2	2	2	1	1	3	2	2	1	1	2	1		1	1	1	1
8	Italy	Mussels	Open system (raceways, flow-through tanks, ponds...)	Marine;	3	3	3	3	3	3	3	3	3	3	3	3	5	3	3	3		3	3	3	5
9	Italy	Mussels	Molluscs on suspension (Longlines, raft, batea…)	Marine;	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1
10	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	3	1	1	4	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	1
11	Italy	rainbow Trout; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	1	3	5	3	5	5	5	3	5	3	3	5	5	5	5	5	5	5	5	4
12	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	1	2	2	1	4	3	4	4	4	4	3	3	3	3	3	3	3	3	3	3
13	Italy	Mussels	Molluscs on suspension (Longlines, raft, batea…)	Marine;	1	1	1	1	1	5	1	1	1	1	1	1	1	1	1	1	1	1	3	1	2
14	Italy	rainbow Trout; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	5	5	1	2	1	2	1	1	1	1	3	1	1	1	1	1	1	1	1	1
15	Italy	rainbow Trout; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	5	5	1	1	1	5	1	1	1	1	5	1	1	1	1	1	1	1	1	1

ID	Country	Species	Type of Farm	Environment	2a	2b	2c	2d	2e	3a	4a	4b	4c	4d	4e	5a	5b	5c	5d	6a	6b	6c	6d	6e	7a
16	Italy	Sea Bass; Sea Bream; Mussels; Oysters; Clams	RAS	Marine;	3	5	4	4	3	1	5	4	1	1	1	4	4	2	5	1	1	1	3	1	5
17	Italy	Mussels; Oysters	Molluscs on suspension (Longlines, raft, batea…); Molluscs on the bottom	Marine;	1	1	3	3	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1	1
18	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	2	2	2	5	5	5	2	5	5	5	5	5	5	5	5	5	5	5	5	5	5
19	Italy	Mussels	Molluscs on suspension (Longlines, raft, batea…)	Marine;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
20	Italy	Eel; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	1	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
21	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	3	5	5	5	5	5	5	5	5	5	4	5	5	5	5	5	5	5	5	5
22	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	3	1	1	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1
23	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	1	1	4	2	2	3	5	5	5	5	5	5	5	5	5	5	5	5	5	5
24	Italy	Rainbow Trout	Other	Freshwater;	3	3	3	3	3	3	1	1	1	1	1	2	2	2	2	1	1	1	1	1	1
25	Italy	Mussels; Oysters	Molluscs on suspension (Longlines, raft, batea…); Raised molluscs (in a container or tables with bags)	Marine;	1	1	1	1	3	1	1	3	3	3	2	2	2	3	2	3	2	2	3	3	2
26	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	2	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
27	Italy	Mussels; Oysters; Clams	RAS	Marine;	3	4	4	2	2	5	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5
28	Italy	Mussels	Molluscs on suspension (Longlines, raft, batea…)	Marine;	5	5	5	5	5	5	2	5	2	2	2	5	3	3	3	2	5	5	3	2	5
29	Italy	Rainbow Trout	Other	Freshwater;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
30	Italy	Mussels	Molluscs on suspension (Longlines, raft, batea…)	Marine;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
31	Italy	rainbow Trout; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
32	Italy	Oysters; Clams	Molluscs on suspension (Longlines, raft, batea…); Raised molluscs (in a container or tables with bags); Open system (raceways, flow-through tanks, ponds...)	Marine; Brackish;	5	4	5	5	5	3	5	5	5	5	5	4	5	5	5	5	5	5	5	5	5

ID	Country	Species	Type of Farm	Environment	2a	2b	2c	2d	2e	3a	4a	4b	4c	4d	4e	5a	5b	5c	5d	6a	6b	6c	6d	6e	7a
33	Italy	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
34	Italy	Other	Open system (raceways, flow-through tanks, ponds...)	Brackish	1	1	1	2	2	3	3	3	3	3	3	2	5	5	4	5	5	5	5	5	4
35	Italy	Mussels; Oysters	Molluscs on suspension (Longlines, raft, batea…)	Marine;	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
36	Portugal	Sea Bass; Sea Bream	Open system (raceways, flow-through tanks, ponds...)	Marine;	1	1	1	1	1	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
37	Portugal	Clams	Molluscs on suspension (Longlines, raft, batea…)	Marine;	1	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1	3	1	1	1	1
38	Portugal	Oysters	Raised molluscs (in a container or tables with bags)	Brackish	1	2	5	1	2	1	3	1	1	1	1	2	1	1	1	1	1	1	1	1	1
39	Portugal	Sea Bass; Sea Bream; Oysters; Clams	Open system (raceways, flow-through tanks, ponds...); Raised molluscs (in a container or tables with bags)	Brackish	4	4	2	4	3	5	5	5	5	5	5	2	2	4	3	5	5	5	5	5	5
40	Portugal	Oysters	Raised molluscs (in a container or tables with bags)	Brackish	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
41	Portugal	Tuna	Sea cages	Marine;	1	1	1	1	1	1	1	5	1	1	1	1	1	1	1	1	1	1	1	1	1
42	Portugal	Oysters	Raised molluscs (in a container or tables with bags)	Marine;	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
43	Portugal	Oysters	Molluscs on suspension (Longlines, raft, batea…); Raised molluscs (in a container or tables with bags)	Marine; Brackish;	1	3	3	1	1	3	1	1	1	1	1	3	1	1	1	1	1	1	1	1	1
44	Portugal	Sea Bass; Sea Bream	Open system (raceways, flow-through tanks, ponds...)	Marine;	3	3	3	3	3	1	3	3	2	2	2	1	1	1	1	1	3	1	1	1	1
45	Portugal	Sea Bass; Sea Bream	Open system (raceways, flow-through tanks, ponds...)	Marine;	1	1	1	5	1	3	4	5	5	5	5	4	5	5	3	5	5	5	5	5	5
46	Portugal	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	5	5	5	5	5	5	5	5	5	5	5	2	5	5	5	5	5	5	5	5	5
47	Spain	Tuna	RAS	Marine;	1	1	2	2	2	5	2	4	3	1	2	3	4	4	4	4	4	4	4	4	4
48	Spain	Sea Bass; Sea Bream	Open system (raceways, flow-through tanks, ponds...)	Marine;	2	2	4	5	3	5	5	5	5	5	5	3	5	5	5	5	5	5	5	5	3
49	Spain	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	4	2	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
50	Spain	Rainbow Trout	RAS; Open system (raceways, flow-through tanks, ponds...)	Freshwater;	4	1	1	1	2	1	1	1	1	1	1	3	1	1	1	1	1	1	1	1	1
51	Spain	rainbow Trout; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	1	2	2	3	1	4	1	3	3	3	3	1	3	3	3	3	3	3	3	3	3

ID	Country	Species	Type of Farm	Environment	2a	2b	2c	2d	2e	3a	4a	4b	4c	4d	4e	5a	5b	5c	5d	6a	6b	6c	6d	6e	7a
52	Spain	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	3	2	2	5	2	5	5	5	5	5	5	4	5	5	5	5	5	5	5	5	5
53	Spain	rainbow Trout; Other	Open system (raceways, flow-through tanks, ponds...)	Freshwater;	4	3	3	1	4	1	5	1	1	3	1	4	1	1	1	1	1	1	1	1	1
54	Spain	Sea Bass; Sea Bream; Meagre	Sea cages	Marine;	2	2	3	5	5	2	1	1	5	5	5	4	5	5	4	5	5	5	5	5	3
55	Spain	Sea Bass	RAS	Marine;	1	2	1	4	3	5	1	4	5	5	5	5	5	5	4	4	5	5	5	5	4
56	Spain	Eel	RAS	Freshwater;	1	1	1	1	2	5	2	5	5	5	5	5	5	5	5	5	5	5	5	5	2
57	Spain	Turbot	Open system (raceways, flow-through tanks, ponds...)	Marine;	1	1	1	5	2	5	5	5	5	4	3	2	5	4	3	5	5	5	5	5	1
58	Spain	Sea Bass; Sea Bream	Sea cages	Marine;	1	1	1	4	4	1	1	1	4	5	5	4	5	5	3	5	5	5	5	5	2
59	Spain	Mussels	Molluscs on suspension (Longlines, raft, batea…)	Marine;	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	4
60	Spain	oysters	Molluscs on suspension (Longlines, raft, batea…)	Marine;	5	5	2	5	5	5	1	5	5	5	5	5	5	5	5	5	5	5	5	5	5
61	Turkey	Sea Bass; Rainbow Trout	Sea cages	Marine; Freshwater	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
62	Turkey	Rainbow Trout	Sea cages	Marine; Freshwater	5	5	2	5	5	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1
63	Turkey	Rainbow Trout	RAS; Sea cages	Freshwater	5	5	5	5	5	3	1	5	5	5	5	5	5	5	5	5	5	5	5	5	3
64	Turkey	Rainbow Trout	Sea cages	Marine; Freshwater	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	1	5	5	5
65	Turkey	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...); Sea cages	Freshwater	4	5	4	5	5	5	4	5	5	5	5	5	5	5	5	5	5	5	5	5	5
66	Turkey	Sea Bass; Sea Bream; Rainbow Trout; Mussels; Other	Open system (raceways, flow-through tanks, ponds...); Sea cages	Freshwater; Brackish	2	2	2	4	4	3	3	5	5	5	5	5	5	5	5	5	5	5	5	5	2
67	Turkey	Sea Bass; Sea Bream; Rainbow Trout; Mussels	Open system (raceways, flow-through tanks, ponds...); Sea cages	Marine; Freshwater	4	5	5	5	5	4	3	3	4	5	5	5	5	5	5	5	5	5	5	5	3
68	Turkey	Rainbow Trout	Open system (raceways, flow-through tanks, ponds...); Sea cages	Freshwater	4	5	5	5	5	5	3	5	5	5	5	1	5	5	5	5	5	5	5	5	5
69	Turkey	Rainbow Trout	Sea cages	Freshwater	4	5	5	5	5	5	3	5	5	5	5	1	5	5	5	5	5	5	5	5	5