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Sustainable aquaculture development: a review on the roles of cloud computing, internet of things and artificial intelligence (CIA)

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Abstract

Each year, there is a significant rise in demand for global food production due to population increase and a rise in demand for protein food sources. This puts pressure on capture fishery as fish is a preferred protein source worldwide. However, the more resources we put into the capture fisheries to obtain maximum catch, the faster the fisheries stock becomes depleted. The best option left to produce enough fish to meet demand is relying on advanced aquaculture. Unfortunately, the impact of technological advancement in the aquaculture sector is not profound compared to the agricultural and manufacturing sectors. The advent of Cloud computing, Internet of Things, and Artificial Intelligence (CIA) has expanded numerous possibilities for applying and integrating information technology in all works of life. This article reviews the emergence of research development on CIA and the potential to revolutionize the aquaculture industry. The use of CIA techniques and tools such as drones, nano and micro-sensors, bionic robots, remote cameras, intelligent sorting, energy-saving processing equipment, statistical modules, and algorithms will reduce human intervention and increase aquaculture productivity. Also, the application of CIA in the aquaculture value chain to ensure effectiveness in traceability, feeding, disease detection, growth prediction, environmental monitoring, market information, and others is key to increasing aquaculture productivity and sustainability. Therefore, the future of aquaculture operations with less human labour, effective maintenance, and resource utilization largely depend on innovative technologies. Here, we outlined the need for adopting innovative technologies and the limiting factors that hinge on CIA adoption in the aquaculture industry.

Key words: aquaculture, CIA (cloud computing internet of things and artificial intelligence), fish health, productivity, sustainability, technology.

Introduction

Each year, there is a significant rise in the demand for global food production due to an increase in population, rising income, increasing awareness of the health benefits, etc. among consumers account for the rise in demand for protein sources. In contrast, climate change and the increase in natural resource extraction put pressure on the fish stock, especially in the wild. Fish and fisheries products provide excellent protein sources compared with terrestrial animal proteins and essential fatty acids, especially long-chain polyunsaturated fatty acids (LCPUFA) and micronutrients (Beveridge *et al.* 2013). According to the Food and Agriculture Organization (FAO), more than a billion people depend on fish as a primary source of animal protein worldwide, with a 20.5 kg per capita average consumption in 2018 (FAO 2018, 2020). The high demand for fish and fisheries products and the inability of the capture fisheries to meet the demand has created a gap between the production-demand chains. However, capture fisheries shouldn't be seen as the primary source of fish for human consumption because global capture fisheries are hugely damaging to marine ecology and biodiversity, requiring a reduction in reliance on capture fisheries.

Aquaculture is the rearing and production of aquatic animals and plants, including finfish and shellfish, for food and non-food purposes. Aquaculture production is mostly under controlled or semi-controlled systems. Therefore, technological applications that allow population densities management and optimizing culture management are currently the one possible solution to ensure production efficiency. Meanwhile, aquaculture contributions to global fish production have increased over the years, reaching 46 per cent in 2016–2018 against 40.1, 42.6, 43.7, 44.7, and 45.1 per cent from 2011 to 2015 (FAO 2018, 2020). Despite this growth, there is still the need for technological advancements to help deal with problems such as water pollution, disease outbreaks, quality of broodstock and fingerlings, and poor management practices (Fearghal 2019; Michael 2019).

To address some of these challenges, innovative technological practices need to be adopted. Interestingly, technologies including the use of IT devices and tools such as drones, autonomous tractors, sensors, robotics, data analysis etc., to enhance efficiency and sustainability in farm management are widely adopted in the agricultural industry than in aquaculture (Brown 2018; Ramin Shamshiri *et al.* 2018). Also, emerging precision agriculture companies are focusing on developing technologies that allow farmers to maximize yields by controlling every variable of crop farming, such as moisture levels, pest stress, soil conditions, and micro-climates (Abdullahi *et al.* 2015). The speed at which technology develops, especially in solving problems by speeding up tasks, removing the need for manual labour, automating routine tasks etc., cannot be overemphasized. Several aspects of technologies are available, from the use of Information Technology (IT) in the areas of Artificial intelligence (AI), Internet of Things (IoT), and Cloud Computing. These provide services such as easy access to a wide range of IT services with no upfront cost (pay-as-you-go), increased speed, shared usage costs with no expenses on hardware, facilities, and power. The development of web-enabled smart devices can collect and share information about their usage and the environment without human interaction (AWS; TechTarget; Mattern & Floerkemeier 2010; IBM 2016).

This review looked at the possible contributions of current technological advancements to the advantage of the aquaculture industry. This review focused on innovative technologies spanning from cloud computing, internet of things, and artificial intelligence, and their implementations in the aquaculture industry.

Cloud computing, internet of things and artificial intelligence (CIA)

Cloud computing

Cloud computing refers to the practice of employing a network of remote servers hosted on the internet for storage, management, and data processing rather than on a local server or personal computer. Cloud computing can be deployed over the cloud, on-premises, or hybrid deployment. It also provides three main service models which represent different parts of the cloud computing components; Software as a Service (SaaS) designed for customers, Platform as a service (PaaS); designed for developers and Infrastructure as a Service (IaaS); designed for system administrator (AWS). Figure 1a gives a detailed visualization of the various types of cloud computing service and deployment models.

In aquaculture, Cloud computing is mainly used to collect data generated from production, processing and sales and store the generated data before processing and analysis (Yongqiang *et al.* 2019). Aquaculturists often follow sets of protocols and guidelines during fish production. Cloud computing and big data technologies make it possible to gather huge data for traceability and method optimization. With the integration of CIA as the key to building a smart aquaculture system to enhance optimal performance, feasibility and flexibility, Cloud computing serves a good platform for application system integration (water quality monitoring system, data intelligent processing system, and fish pest knowledge base). One such case is a cloud-based platform known as Aquacloud developed by the Seafood Innovation cluster in Norway, in partnership with IBM and several other companies. The platform is built on IBM Clouds to capture sea lice counts and other data from aquaculture companies. The data is then passed into a predictive model for forecasting sea lice outbreaks over time. This information is then presented to farm managers to help them understand the risks at stake and take preventive measures before an outbreak (Hoel 2018).

Internet of things (IoT)

The internet of things refers to the concept of creating a network of physical computing devices capable of information gathering and sharing. It is a network consisting of web-enabled 'smart devices' capable of collecting and sharing information about their usage and environment without human interaction. These devices use embedded systems such as built-in sensors, processors and communication hardware and can also apply artificial intelligence such as machine learning for easy data processing and understanding (Mattern & Floerkemeier 2010; Dupont

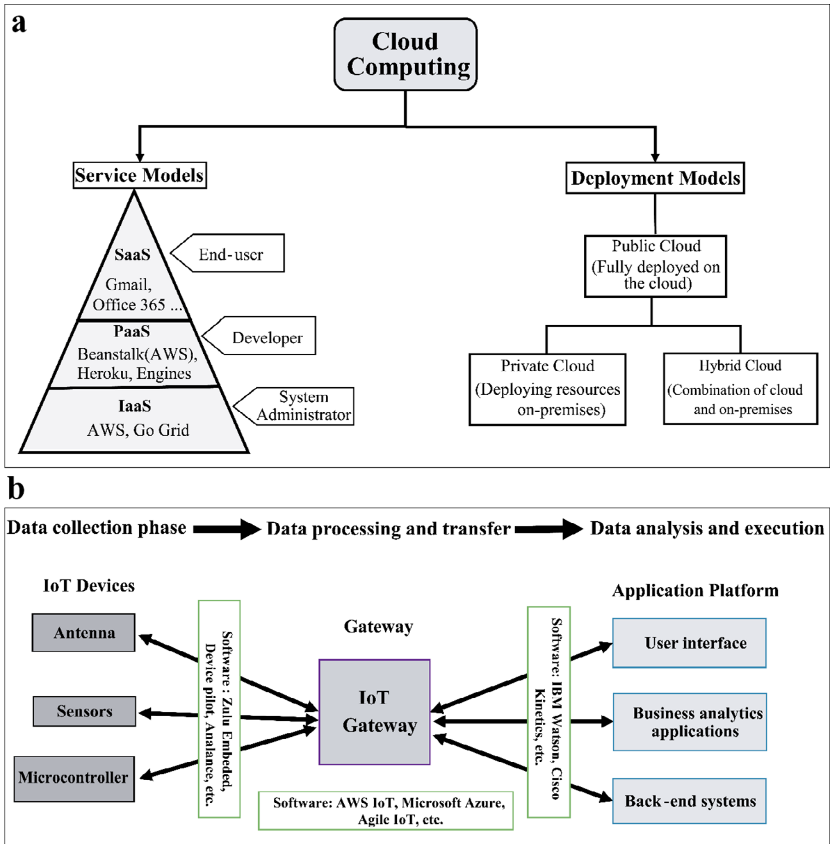

Figure 1 (a) Cloud computing and (b) internet of things (IoT) models AWS, Amazon web service; IaaS, infrastructure as a service; PaaS, platform as a service; SaaS, software as a service, (Sources (Atzori *et al*. 2010; AWS; Sourceforge 2020)).

et al. 2018; TechTarget). Figure 1b depicts a typical composition of an IoT system.

The use of IoT is fast developing in the agriculture industry to achieve high precision farming and high yield. However, its use in the aquaculture industry is now gaining recognition. The risk involved in the aquaculture industry is higher due to high uncertainties in water bodies coupled with a combination of effects from climatic variables, such as, global warming, drought, flood, salinity cyclone, rainfall variation, ocean acidification, and sea-level rise. This makes it quite challenging to replace human intervention with an automated IoT system wholly. A recent report indicates that AI and machine learning processes can pre-define aquaculture operational to eliminate or minimize risk with the interconnection of IoT devices (Yang *et al*. 2020a). Therefore, automation of the aquaculture industry with the use of improved IoT devices such as; bionic robots, remote cameras, micro-and nano sensors, intelligent sorting and energy-saving processing equipment for aquatic products would help in areas such as; operation production, monitoring fishery, monitoring environmental conditions, automatic inspection etc., to save labour and increase productivity. However, in settings, most IoT devices are interconnected and need to communicate via networking.

An example is the ‘OxyForcis’ designed and manufactured by ‘Smalle Technologies’, which is currently operating in both fresh and marine water in Spain to measure temperature and oxygen levels. The measurement is done with an optical sensor placed inside the cage/pond, and the readings are displayed on an electronic unit attached to the pond/cage. The electronic unit can also send the data via a remote server on the internet using wireless communications at user-defined intervals and receive on users’ phones or computers for necessary action to be taken (Martin 2019).

Despite this, much is needed on information transmission technology to ensure effective connectivity, efficiency, reliability, accuracy, and secure network communication with IoT devices considering the aquaculture environment. Interestingly, Li and Li (2020) outlined six (6) important requirements necessary for the effective networking of IoT aquaculture in future; (i) all network equipment in farm having access to network not limited by geographical location or time. (ii) achieving high transmission rate peaking up to 100 Mbps ~ 1 Gbps (5G technology), positioning accuracy to centimetre level, and reducing network delay to a microsecond. (iii) reduction in network interruption with high reliability and high density of 100 equipment connections per cubic metre. (iv) ability to support multi-network integration, business integration etc. (v) ability to support deep integration with new technologies such as AI, and (vi) the ability of the aquaculture information transmission technology to resist network attacks and trace sources of attacks.

Artificial intelligence (AI)

A field in computer science that aims to equip machines with learning mechanisms that can enable them to make decisions based on past experiences by mimicking the cognitive functions of living things. With AI being the broader science of mimicking natural behaviour, machine learning. One of the specific scientific methods currently applied for AI development involves studying algorithms and statistical models used by computer systems to perform specific tasks with minimal human interference (Russell *et al.* 2016). In machine learning, algorithms are used to build mathematical models based on trained data to make predictions without being specifically programmed to perform the task. The value of Machine learning technology has been recognized by most industries that deal with large amounts of data in order to improve efficiency. Machine learning methods can be classified in several ways but are mostly differentiated between supervised and unsupervised learning. With supervised learning, the learning algorithm is fed training data containing inputs and desired output, whereas, in unsupervised learning, patterns from data are learned automatically without human intervention (Bhattacharyya & Kalita 2013).

The key recognized paradigm of AI is solving problems by interpreting an automated intelligent task. The use of AI models (e.g., modern data science methodologies) is fast developing in other fields. Simultaneously, within the aquaculture sector, they have not been sufficiently harnessed (Yang *et al.* 2020a). In today's aquaculture, digitalization, big data, and deep learning (DL) present an opportunity to apply machine learning techniques in developing models to predict unforeseen occurrences and ensure efficiency in decision-making. DL employs large amounts of data to analyse and interpret the data into smaller concepts (Bengio *et al.* 2013; Schmidhuber 2015; Yang *et al.* 2020b). DL in smart fish farming has been thoroughly reviewed under live fish identification, species classification, behavioural analysis, feeding decisions, size or biomass estimation, and water quality prediction, generating high accuracy results than traditional methods (Qin *et al.* 2016; Meng *et al.* 2018; Naddaf-Sh *et al.* 2018).

In effect, to utilize AI and machine learning, problems are identified and fed into machine learning processes as intelligent tasks, which are then processed and interpreted into comprehensible form for decision-making. Fortunately, machine learning can process and interpret multiple tasks faster and quicker than relying on experts, which will also be a relief and less worry over processing multiple tasks. By using multi-source data, Yang *et al.* (2020) proposed an approach to defining operational limits in aquaculture to provide industries, especially the service companies, support to make safe operational planning and decisions for both coastal and offshore fish farms. They employed machine learning such as Bayesian network, Tree Augmented Naïve Bayes (TAN), and algorithms to build up a prediction model to decide operational limits at a given condition.

Because AI presents an opportunity to solve issues driven by experience and background knowledge to obtain relevant information and make discoveries, which previously rely on experts' experience. There is a need for research development to improve statistical models and algorithms under AI and machine learning to ensure high accuracy (99.99%) in prediction by eliminating external influence. However, in migrating to machine learning techniques, we can't avoid trade-offs. Therefore, we should expect to deal with unforeseen occurrences during the transition period, at least for a short while.

Trends in CIA

In IoT, the explosive growth of interconnected devices over the internet has been a significant trend in recent years (Nordrum 2017). Even with the wide range of applications of these devices (Consumer, Industrial, Infrastructural, Organizational, Product digitization as well as Military applications), they still share basic characteristics (e.g., IoT devices use MOSFET (metal-oxide-semiconductor field-effect transistor, or MOS transistor) (Perera *et al.* 2015; Vongsingthong & Smanchat 2014)).

Since the inception of the idea of a network of smart devices as far back as 1959 (Palermo 2014; Universitry 2018), the biggest concern for adopting IoT technology to date involves safety, security, and privacy (Feamster 2017). Hence government bodies and other agencies continue to develop regulations to curb these concerns. Examples include recommendations submitted by the Free Trade Commission of the United States in 2015 on data security, data consent, and data migration (Mason Hayes & Curran 2016). As well as the senate bill no. 327 which went into effect on January 2020 in the US. The bill states that 'a manufacturer of a connected device, as those terms are defined, to equip the device with a reasonable security feature or features that are appropriate to the nature and function of the device, appropriate to the information it may collect, contain, or transmit, and designed to protect the device and any information contained therein from unauthorized access, destruction, use, modification, or disclosure' (Porcelli 2020).

With the convergence of CIA, the provision of anytime-anywhere access to data and data analytics through Cloud servers makes cloud computing a necessity for easy analysis of IoT data by companies. AI has been the primary driving force behind the full potential of IoT technology, as it serves as the brain behind automated data analysis collected by IoT devices. In 2017, the number of IoT devices increased to about 8.4 billion. With the learning capabilities offered by AI in IoT technology, the estimated growth of IoT devices to be about 30 billion by 2020 was predicted (Hsu & Lin 2016; Nordrum 2017).

With the latest technological trends driven from CIA, aquaculture hasn't been left out totally in this niche. CIA has been gaining recognition in aquaculture recently as the application of autonomous environmental monitoring devices in inspection and crowd control of sea lice infestation (Føre *et al.* 2018), data-driven water quality sensors, Augmented reality (AR) devices as well as web applications and servers are being proposed, designed and implemented in the aquaculture industry to enhance and automate real-time decision-making processes that posed as challenges in farm operations. We discussed herein some specific cases of these trends in aquaculture below:

A data-driven android application known as 'mKRISHI® -AQUA' for aquaculture farm management was proposed and developed by (Piplani *et al.* 2015) to help speed up farm operations in India. Their application supported data collection, processing and presentation through steps from registration of farms, creation, management, and report of pond data.

Since water quality is very essential in selecting a suitable site for aquaculture and also for maintaining the suitability of the site, several water quality parameters (Temperature, dissolved oxygen, pH, salinity and turbidity) needs to be in constant check to ensure they are environmentally suitable for the survival of aquatic species in order to ensure fish welfare and enable them to grow and perform according to their potential. Therefore, an end-to-end software service application for Aquaculture Resource Planning System (ARP) and development was proposed by (Shetty *et al.* 2018) to tackle the issues of time consumption as well as measurement efficiency that exists when it comes to the measurement of water quality parameters. Their system consists of an integration of a Wireless Sensor Network (WSN) based on Zigbee protocol for water monitoring and a cloud-based approach (SaaS) for data collection and processing in order to determine the suitability of the site. Unfortunately, we are unable to verify the progress of this research at present, however, other similar researches have been conducted including the work of (Gao *et al.* 2019) where they developed an IoT-based intelligent fish farming tracking control system. Their system provides a forecasting method with automatic water quality management, support for tracking breeding and sale of freshwater fish and also provides historical farming records to consumers through qr code tag on a product.

Also WSN water quality monitoring system using a single chip computer technology as base station where data is transferred was developed by (Simbeye & Yang 2014). They employed the Zigbee protocol for data transfer. The collected data is processed using LabVIEW software and can be forwarded via SMS services to appropriate receivers. Their system showed great prospects for real world use. Simbeye (2018) also presented a WSN based solar powered harvesting system for aquaculture. The aim of the research was to tackle the constraints of replacing or providing enough power to wireless sensors which are often deployed in inaccessible places. They developed a solar oxygenation system for powering remote sensor nodes used in water quality detection and aerators for aquaculture oxygenation. They also included a maximum power point tracking (MPPT) algorithm that could switch power source according to light conditions, this algorithm ensures continuous stable operation.

A time series classification system for predicting the closure of shellfish farms was investigated by (Shahriar *et al.* 2014) they employed feature extraction methods to predict closing or re-opening of shellfish farms by identifying features of both univariate and multivariate time series for rainfall and river flow. Two techniques each were considered for both univariate and multivariate time series: Autocorrelative function (ACF) for extraction of features and Piece-wise aggregate reduction (PAA) for dimension reduction were used for univariate time series with rainfall as the environmental variable. For multivariate time series, they employed Cross-correlation function (CCF) for feature extraction and Principal Component Analysis (PCA) for dimension reduction with rainfall and river flow as environmental variables. At the end of their study, their results demonstrated that time series without the use of feature extraction methods delivered inaccurate results to determine closure while the accuracy of 30% was achieved by applying ACF to rainfall in univariate time series and in multivariate time series, an accuracy of 25% was achieved using CCF and PCA over features extracted from rainfall and river flow. This result doesn't seem to be impressive, further research is therefore necessary to increase the accuracy in predicting future closure times.

The application of machine learning techniques for data analysis was considered by (Rahman & Shahriar 2013) in their work. They developed an influenced matrix-based approach for selecting relevant environmental features and used these features for prediction of algal growth. They employed different regression algorithms for the prediction to determine their relative strength. At the end of their experiment, they concluded that using influence matrix-based feature selection approach generates more accuracy of algae growth prediction than using all the features. Promisingly, this system could be used for the advance prediction of algal bloom in the aquaculture industry.

Length and weight parameters in many fisheries are required in identifying fish growth, mortality, reproduction, and recruitment. Obtaining these data in most cases is time-consuming and can lead to stress or injury to fish since the fish has to be taken out from the water for measurement to be taken. There is, therefore the need to employ advanced techniques to overcome these challenges. Interestingly, the use of CIA has shown a promising future in this aspect. Reports indicated that, the accuracy of measuring fish length by processing an underwater fish image ranges from 95% to 99.81% (Rahim *et al.* 2010; Mustafa *et al.* 2013). The difference in accuracy could primarily be due to the differences in methodologies and algorithms used. Similarly, several regression algorithms and image processing techniques were used to calculate length, and weight estimated from processing underwater fish images. However, the time taken for an image to be processed varies amongst different algorithms (1.26–3.30 s) and even with the same algorithm but different methods (bilateral filter and guided filter method) (1.56–1.26 s) (Sanchez-Torres *et al.* 2018). Therefore, for any system to be widely used, many algorithms and models need to be considered and the optimum chosen.

Deploying CIA in aquaculture

Even though the aquaculture industry precedes the agriculture industry in terms of adoption of innovative technologies. The aquaculture industry is developing rapidly in recent years, coupled with the development of new technologies that are gradually transforming aquaculture from traditional labour-intensive farming to mechanized aquaculture and slowly to automated systems (Li & Li 2020). The CIA can fix defective performance issues and inadequate information in understanding large and diverse big data in aquaculture to achieve smart data processing and analysis and enhance decision-making in intelligent aquaculture (Yang *et al.* 2020b). The adoption of technologies in salmon aquaculture, the recirculating aquaculture systems (RAS), biofloc, and others are pioneering the development of the aquaculture industry;

Recirculating aquaculture systems (RAS)

In this system, water is continuously disinfected and reused in a closed circuit by removing or converting solid waste (ammonium and CO_2) into a non-toxic product and re-oxygenating the water. The use of RAS has reduced the demand for labour with a subsequent increase in production. Like any other technology, the RAS venture is also faced with challenges. In the United States, catfish and trout production is characterized by developing profitable and efficient production management strategies. While a high rate of failure has characterized the commercial RAS ventures, the reason for this is attributed to large amounts of investment capital required with long payback periods. Also, its production mode requires much-skilled personnel, thereby affecting cost-effectiveness (Engle *et al.* 2020; Li & Li 2020). Engle *et al.* (2020) proposed that similar catfish and trout production interventions be applied to RAS in the United States. The RAS is capable of reusing ≥90% of the culture water (Moreno-Andrés *et al.* 2020). The loss of water could be attributed to the fact that the RAS system has several components. Water is lost through evaporation and drum filter backflushing during the recycling process. Interestingly, to compensate for the water deficit, another system has recently been developed (Membrane Bioreactor (MBR)) to treated domestic wastewater for reuse (Gukelberger *et al.* 2020).

Salmon aquaculture

Technologies used in salmon aquaculture have been developing tremendously in recent years. Four major technological advancements used in Canada's salmon production were identified as (i) land-based RAS, (ii) hybrid systems, combining land RAS production of post-smolts with marine grow-out to market size, (iii) floating closed containment systems and (iv) offshore systems involving open or closed containment systems. These systems offer an opportunity for the future development of the aquaculture industry. These main systems involve supporting technologies such as sensors, artificial intelligence, remote-operated vehicles, and others for efficient operation (FOC 2019).

These technologies are pivoted on their ability to either monitor water quality in real-time or maintain water quality. This indicates that water quality is paramount to the success of aquaculture and therefore should be monitored at all times. Although remote sensors are necessary for the RAS and salmon cage farming, cloud computing and artificial intelligence are not widely adopted in these areas.

Areas of CIA applications

Identification and measurement

In terms of species identification, factors such as visual characteristics as well as sound frequencies can be employed by DL to provide accurate results as DL models are capable of learning unique visual characteristics of species that are insensitive to environmental changes and variations (Dos Santos & Gonçalves 2019). Deep leaning DL has been applied to provide a more accurate estimation of fish morphological features, including length, width, quantity, abundance, and other areas. Observation of these features is essential to enhance fishery management production (Saberioon & Císař 2018; Li *et al.* 2020a).

Sampling

In terms of quantity, traditional artificial sampling approaches have proven to be time-consuming and complex, and strenuous on fish. Zhang *et al.* (2020) proposed an automated fish counting method based on resolving the aforementioned issues and providing real-time, accurate and lossless counting of fish populations in far offshore salmon mariculture. They constructed a hybrid neural network model; A multi-column convolution neural network used as a front end for capturing feature information of various receptive fields. A wider and deeper dilated convolution neural network is used as the back end to reduce the loss of spatial structure information during network transmission. Experimental results show that the counting accuracy of the proposed hybrid neural network model is up to 95.06%.

Monitoring

Monitoring of the aquaculture environment is important due to high variability, especially in the open sea, which can pose a tremendous threat to aquaculture. Traditionally, it is difficult and time-consuming to and sometimes risks the cultivated species if anomalies in water quality are not detected on time. Real-time monitoring of the environment, water quality (dissolved oxygen, temperature, pH, ammonia chlorophyll, nitrogen, nitrite, etc.) and fish behaviour is necessary for the aquaculture managers to make a timely intervention and reduce risks. Monitoring of the aquaculture environment can employ sensors, drones, buoys, underwater robots, online remote monitoring equipment, etc. Wind speed and wind direction, wave height, ocean current velocity can also be obtained offshore (Devi *et al.* 2017). Real-time online monitoring technology has been introduced in cage culture to monitor water quality parameters to improve efficiency and reduce culture risks (Raju & Varma 2017). The aspect of water quality monitoring is receiving much attention, and several other technologies have been proposed and developed (reviewed in ref. Wei *et al.* 2020). Besides, fish behaviour gives much information on the response of fish to the ambient environment. Behavioural change of fish is an indication of the combined effect of environmental fluctuations and stress on fish. Machine vision, acoustic or sonar technologies can be used to obtain fish behaviour such as feeding behaviour, swimming behaviour, stress response, fluctuations in fish population etc., (Bae & Park 2014; Føre *et al.* 2018).

Feeding

Feeding is a major determinant of production costs and water quality in aquaculture (Li *et al.* 2020b). In other to reduce cost and save time, most large-scale farming resorts to automatic feeding techniques. Automatic feeding machines operate on a timely basis; it feeds only when the time is due to feed irrespective of the water condition. Therefore, using automatic feeding machine can cause overfeeding and alter water quality (Liu *et al.* 2014). Applying technologies such as data fusion and deep learning has a high potential for enhancing fish feeding behaviour recognition (Li *et al.* 2020b). In a system where fish feeding is automated, the feedback on environmental monitoring technology is interlinked with an automatic feeding control system. This allows for the control of feeding in the culture systems, making it possible for feeding to be adjusted or halted based on the water quality or fish behaviour.

An example is the Akvasmart CCS feeding system from AKVA Norway. The system is equipped with a Doppler residual feed sensor, environmental sensor, aquaculture video camera, and other monitoring systems to monitor the underwater environment and achieve accurate feed dose control. The system has the capacity to handle >40 feed lines operating in parallel and >1000 tanks/unit, all of which is operated from a PC or a smart device (phone or iPad) (Wei *et al.* 2020).

Disease detection

A broader range of disease-causing organisms from bacterial, fungal, parasites to protozoan exist. Some diseased fish show various external signs that range from ulcers, exophthalmia, and emaciation to lethargy, visible granulomas, or no signs at all. Some nematoda can be found externally (e.g., hookworms). Some external signs of diseases include; change in skin colour, swelling of head, bulging eyes, eroded fins, gills, and/or sores on the body, etc. Adopting CIA techniques has been shown to detect fish diseases by recognizing most external abnormalities in fish. Most of the techniques for disease diagnosis are established on the principles of pattern recognition, with three main tasks identified: (i) segmentation, which aims to separate the lesions from the rest of the image; (ii) feature extraction, which aims to extract as much information about the region of interest (usually lesions) as possible; (iii) classification, whose function is to combine the information present in the features into a reliable identification of the disease (Barbedo 2014).

A typical example is the monitoring technology developed by IPI under Singapore's ministry of trade to detect fish diseases. The technology uses a 2D or 3D camera to capture fish behaviour (the detailed outlook and trajectory of the fish for diseased symptoms on fish scales) illuminated by near-infrared light in small tanks and cages. The camera measures reflected infrared light and light intensity from the fish to correspond to its depth. This helps in the detailed identification and analysis of unique fish skin patterns for behavioural changes (IPI Singapore 2019). Similarly, an IoT-based smart aquaponics system that combines aquaculture with hydroponics for real-time environmental monitoring and disease detection of aquatic leaf and plants using machine technology was developed (Barosa *et al.* 2019). By adopting the CIA, fish diseases that are detrimental and likely to cause colossal havoc will be timely identified and remedied to prevent future loss.

Contribution of CIA in the aquaculture value chain

Implementing truly resilient technology-based solutions across every industry's value chain requires a fully functional network (supply chain) with services that enable traceability and transparency. Therefore, an effective network that empowers the stakeholders with all the right information to enhance real-time data-driven decision-making is required. Technology-based solutions like CIA remedy challenges such as inconsistencies, maintenance, contamination, audits, and quality in the product traceability and transparency supply chain network. Coupled with a secure and reliable cloud storage solution, IoT devices collective with AI can improve the ability to accurately track and monitor product status at selected stages in the aquaculture value chain (Fig. 2a). Providing real-time data insight, faster issue identification and resolution, and ultimately improved operational efficiencies.

CIA in aquaculture has seen significant implications across the aquaculture value chain, especially with the adoption of cloud-based traceability systems that provide easy access to product quality demands and customer awareness. These include continuous measurement of product transport and storage conditions, monitoring disease transmission, weather prediction, feeding, and market information at broader geographic areas. European Union proposed regulations that require the disclosure of information across the food value chain. Also, proposals and studies on fishery and other food products have focused on tracing data in the food value chain to improve customers' information and ensure faster recalls when the need arises (Da Cruz *et al.* 2019). Yan and colleagues designed and developed an aquatic food supply chain traceability platform based on radio frequency identification (RFID) and electronic product code (EPC) internet of things. Their platform provides consumers, enterprises, and government access to tracking, traceability, recall, and monitoring of tilapia products in the food supply chain. The forum is divided into several stages: monitoring information flow (from breeding, production, processing, and distribution to sale); production information management system; water quality monitoring, early disease warning to facilitate quality supervision and; consumer inquiry and complaint platform (Yan *et al.* 2012). These days, consumers and institutions increasingly demand transparency throughout the value chain of food products, including

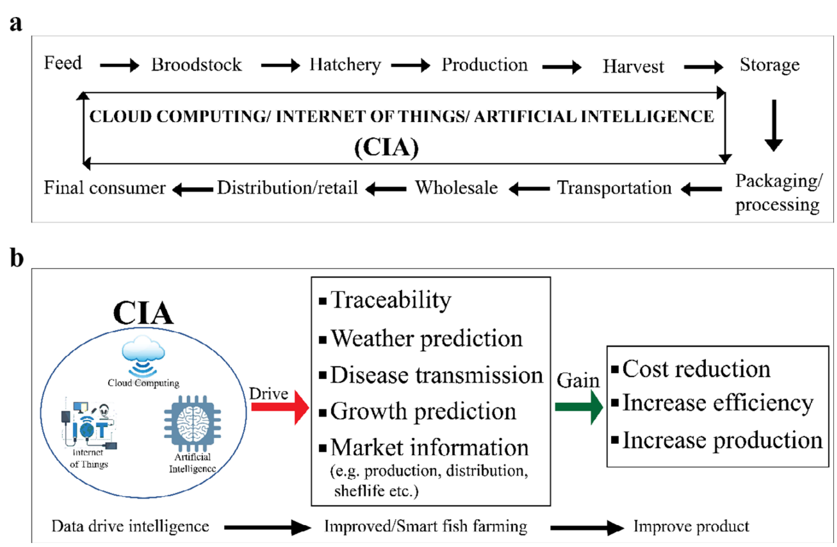

Figure 2 Cloud computing internet of things and artificial intelligence in aquaculture (a) Application of CIA in the aquaculture production line. (b) The drive of CIA in smart farming to increase productivity.

fish. Besides public health reasons, proper traceability is necessary to provide vital information on the origin of fish, batch and whether it has been properly stored and transported, and the current location at any point in time (Cruz & da Cruz 2020). The traceability system allows back and forth tracing fish lots throughout the entire fisheries value chain.

The CIA's application in the aquaculture value chain has also given rise to various startups and companies seeking to harness the benefits of CIA to develop improved aquaculture systems. These companies use the CIA's combined effect in traceability, detecting diseases, weather prediction, growth predictions, market information, etc. (Fig. 2b). An example is the XpertSea, a company that leverages AI and computer vision to provide farmers with advanced data on growth (quantity, size, and weight) of shrimp, hence helping farmers predict the most profitable harvest periods. XpertSea employs deep learning and machine learning to pinpoint growth time frames based on historical growth cycle data. The system provides farmers with actionable, data-driven insights throughout the whole production cycle. It also helps with access to fast payments, a valuable network of buyers and sellers, and industry experts with customer services (XpertSea). 'Observe technologies' uses state-of-the-art AI algorithms to monitor and report anomalies in cage behaviours and feeding patterns to minimize food waste (Observe Technologies). Also, another company provides platforms for the purchase and sale of fish and fish feed (eFishery). With diseases being one of the significant drivers of cost in aquaculture, companies like Aquacloud and Aquaconnect leverages the power of AI to address issues of disease outbreaks before they occur by collecting and processing data and applying preventive measures (The Fish Site). Projects like Shoal under the European research project seek to employ IoT to develop several robofish with the ability to search, monitor, and test water pollution in real-time. This development focuses on critical areas, including advanced intelligence individually and in a swarm, robotic design for efficient aquatic environment interaction, in situ chemical analysis, underwater communication, and computational fluid dynamics (Roboshoal).

Appropriate prediction on weather and water environment may avoid the financial loss caused by flooding from excessive rainfall, inappropriate water quality parameters such as DO, pH, etc. Even the most minor advancement in predicting weather change can produce massive improvement in decision-making. AI and data science technologies like machine learning and data mining bridge the gap between prediction using numerical models and real-time guidance by improving accuracy and efficiency. Researchers at the United States National Oceanic and Atmospheric Administration (NOAA) researched using artificial intelligence to enhance real-time decision-making for high-impact weather. The authors focused on predicting storm duration, severe wind, severe hail, precipitation classification, forecasting for renewable energy, and aviation turbulence, also applicable in the fisheries sector. They also discussed how AI techniques could process 'big data', provide insights into high-impact weather phenomena and improve our understanding of high-impact weather for decision-making (McGovern *et al.* 2017). Many weather sensors and stations are available to predict weather conditions over time (Rikasensor). A three-dimensional approach aiming to predict DO in crap aquaculture pond for a short-term was developed. The prediction model was based on backpropagation artificial neural network (BPANN) optimized by particle swarm optimization (PSO), coupled with the Kriging method. Their results from the validated experiment were satisfactory, with an average error of 0.0705 (mg/L) (Chen *et al.* 2016), opening a chapter for advanced research and optimizations.

Challenges of deploying CIA in aquaculture

Despite the combination of CIA as well as other intelligent aquaculture technologies for use in aquaculture industry throughout the production cycle of an aquaculture system (Engle *et al.* 2020), as well as provision of solutions including but not limited to environmental prediction and early warning, disease diagnosis (Govindaraju *et al.* 2020), behaviour anomaly detection and analysis (Lu *et al.* 2018), quality control and traceability (Freitas *et al.* 2020) market analysis and mining (Purcell *et al.* 2018), several challenges remain:

Internet security

Regardless of the benefits the application of CIA is bringing in Aquaculture, it is impossible to overlook the significance of security and privacy in the interconnected system. IT security issues can arise due to the massive exchange of data between users and service providers. Also, the digitalization of the complete value chain requires companies to share information and decentralize the decision-making process, which is a significant change in many industries' management structure (Martin 2019). However, cyber-attacks such as Distributed Denial of Service (DDOS) and Man in the middle attacks can cause data loss or reduction in data quality, slow automation process, affect service reliability, etc., and subsequently affect future management decisions. Since the adoption of CIA comes with a cost, security issues could reduce the cost-effectiveness. To tackle threats and vulnerabilities to devices and sensitive data in the cloud and IoT environment, a much-focused R&D is paramount. Since the idea of networking devices is still in progress, security has not been considered thoroughly in product design with devices sold with outdated and unpatched software (Stergiou *et al.* 2018), making these devices susceptible to cyber-attacks (Gupta *et al.* 2020). On the other hand, the use of heterogeneous interconnected devices has been identified as vulnerable to cyber-attack, including the ability to control sensors and remote vehicles (Stergiou *et al.* 2018).

Complexity and biodiversity of the aquatic environment

The complex nature of aquatic environments and the biodiversity of aquatic animals make data acquisition still a challenge, leaving most research carried out in laboratories. Hence making large-scale data collection and sharing a setback, especially with Video image acquisition for fish anomaly detection. Another challenge that affects large-scale data acquisition is the inadequate intelligent models for data analysis and the aquaculture industry chain correlation. The application aspects of artificial intelligence such as deep learning (DL) in aquaculture has shown to be successful with most review results concluding that the most significant contribution of DL in aquaculture is feature extraction. however, since DL requires a large amount of training data, its implementation in aquaculture is still a bottleneck as acquisition and sharing of big data in aquaculture still an issue. Also, due to fish's free-swimming nature, fish behaviour classification using deep learning is hindered by crossing and overlapping fish and low-quality environmental images of fish (Zhou *et al.* 2018).

Instability of fish species and environment

The issues of the delicate nature of fish species (sensitive, prone to stress, and freedom of movement) and the uncontrollable state of their environment in terms of lighting, visibility, and stability, make the implementation of Information technologies more difficult. Meanwhile, the strength and reliability of IoT devices are essential to prevent interruptions in automation processes in fish farms. That is notwithstanding, another area of research is concentered on techniques for troubleshooting IoT devices used in the aquaculture industry. Even though this troubleshooting requires efficiency, the research is still in the preliminary stage, and further research will improve the accuracy and integrity of these systems (Li & Li 2020).

Green and dirty water

The aquaculture environment is wide, from clean and clear waters to muddy/dirty or green water. Change in water colour to green (excessive algae growth) results from excessive nutrients such as phosphorus or fish waste. Muddy and green water do not only deprive some cultured fish of favourable conditions for growth and survival (e.g., deprivation of dissolved oxygen) but also make it difficult for underground imaging. It is therefore, necessary to monitor and control the water quality of the culture facility. However, this can only be done in a controlled environment, taking into account the various types of aquaculture (subsistence aquaculture, small-scale commercial aquaculture, small to medium enterprise aquaculture and industrial aquaculture), which could determine the level of intervention.

On the other hand, efforts are being made to solve this issue. Mahmood *et al.* (2020) trained an object detector known as YOLO V3 to tackle the problems of limited training data, multiplex body composition of organisms and hard-to-reach local aquatic environments. Their detector used synthetic data to detect partially visible lobsters in challenging underwater images. Conversely, we are not oblivious of the importance of green water in the aquaculture industry. Growing fish in green water are means of ensuring nitrification and DO through algae growth. In China, developing aquaculture in light of green growth is gaining much attention due to its recognition for environmental protection and high productivity (Zou & Huang 2015). Therefore R&D is needed to optimize underwater cameras' ability to obtain a more precise image in green water.

Determinants of CIA adoption in aquaculture

An important factor affecting the adoption of CIA is the cost of production and adoption. The high cost of production of new technologies affects the cost of implementation and the subsequent cost of acquiring that technology. Production companies will always maintain a reasonable selling price of a product to sustain the company, which affects the production capacity. When the production cost is high, the selling price increases, affecting the affordability and adoption rates. Meanwhile, adopters of new technologies always take into account the cost-benefit of that product. The cost-benefit analysis is vital in a farmer's decision to adopt new technology (Katiha *et al.* 2005). And since the cost-benefit assessment is made before committing to new technologies, the adopters' perceived high-cost prices could be attributed to low rate of technology adoption in the aquaculture industry. Aside from the cost-benefit factor, other impeding factors such as complex technology, limited knowledge of the use of technology, difficulties in accessing the technology etc. could also be attributed to the retardation of the adoption of CIA in the aquaculture industry (Fig. 3).

Taken together, adopting CIA in the aquaculture industry demands a complete understanding of the type of

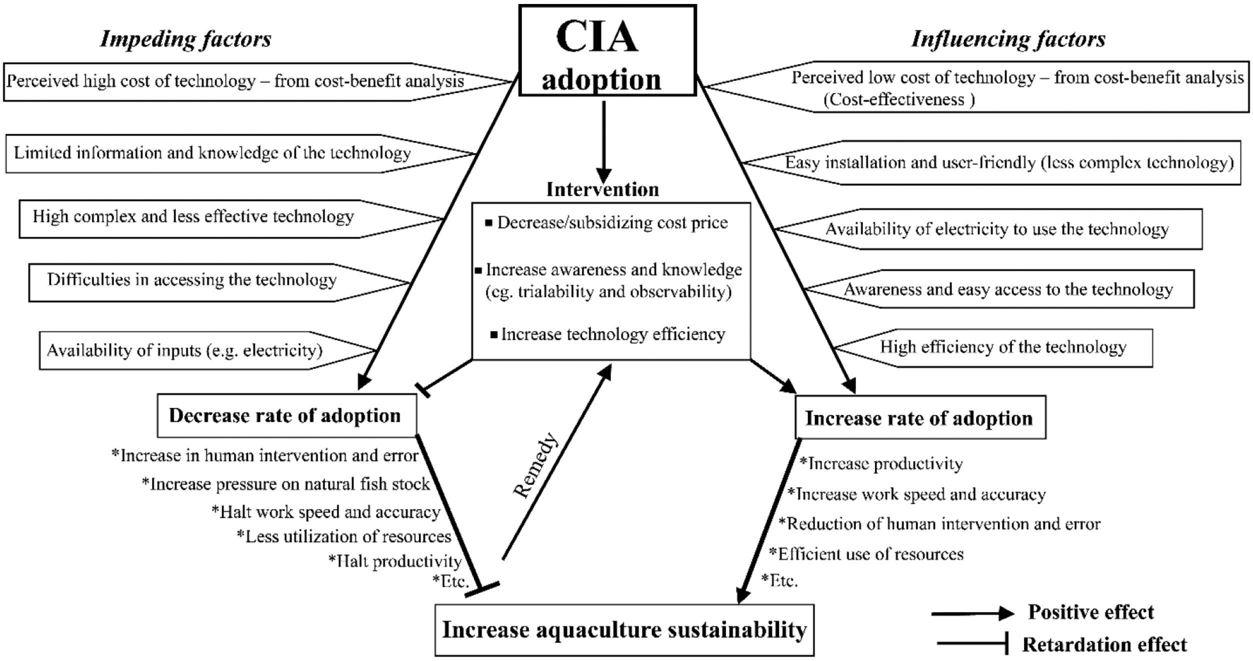

Figure 3 Factors impeding and influencing the adoption of CIA and their effect on aquaculture sustainability. The impeding factors could be attributed to the less adoption of CIA in aquaculture. This could be remedied by appropriate intervention measures to increase adoption and subsequent increase in sustainability.

technology and its associated benefits. The combined effects of impeding factors significantly affect the adoption of CIA in aquaculture. On the other hand, to ensure sustainability, activities to increase the influencing factors should be prioritized (Fig. 3). Since the use of CIA is not an ancient practice in the aquaculture industry, its acceptability is discretionary. Therefore, users must be convinced outright of the ability of a particular technology to solve their problems to increase adoption.

Challenges in adopting innovative techniques

Proposing and developing innovative technology is one thing, while its adoption is ultimately a different issue. When a new technology immerges and is validated through scientific testing, its adoption sometimes becomes challenging. The adoption of new technology is described as an innovation decision-making process, where an individual enters the decision-making stage of adoption or rejection through the first understanding of the time of innovation and confirms the decision (Mwangi & Kariuki 2015; Miranda *et al.* 2016). Like any other industry, the decision for aquaculturists to adopt innovations involves risks, hence the need to convince potential users of the superiority of the new technology over the existing ones (Mwangi & Kariuki 2015). There is no technique without drawbacks. Among others, one of the major obstacles is convincing users to adopt new technologies. Such is the case during the implementation of the biofloc technology (Crab *et al.* 2012). Therefore, understanding the factors that influence the choice of decision is essential for both economists studying the determinants of growth and for the inventors and disseminators of such technologies (Hall & Khan 2002). In addition, three main reasons for non-adoption of technologies by fish farmers in Nigeria were found to be, fund, the effect of the technology, and skill/manpower to use the technology (Ogunremi & Oladele 2012). Similarly, Mwangi and Kariuki (2015) noted that technological, economic, institutional and human-specific factors were determinants of agricultural technology adoption, with the perception of farmers towards new technology being a key precondition for adoption to occur(Mwangi & Kariuki 2015).

Besides, several factors could promote the implementation of a technique; thus, the robustness or effectiveness of the technology over the previous way of doing things. A typical example is the Biofloc technology. This technique enhances water quality in aquaculture by balancing carbon and nitrogen in the system by recycling waste nutrients such as nitrogen into microbial biomass for use animals being cultured or harvested and processed as feed ingredients (Kuhn *et al.* 2010; Crab *et al.* 2012). The system reduces water utilization and waste generation, providing nutritious food sources and improving feed utilization efficiency based on in situ microorganism production (Bossier & Ekasari 2017; Emerenciano *et al.* 2017). In this system, three factors were recognized; Firstly, because water has become scarce or expensive to the extent of limiting aquaculture development. Secondly, the release of polluted effluents into the environment is prohibited in most countries. Thirdly, severe outbreaks of infectious diseases leading to more stringent biosecurity measures, such as reducing water exchange rates (Crab *et al.* 2012). However, the ability of the biofloc technique to remedy these situations was probably the reason for its acceptance by the aquaculturists.

Aquaculture development is directed towards an environmentally friendly approach and biosecurity (Emerenciano *et al.* 2013, 2017). Even though the biofloc system is developing and being employed on a large scale, the mechanisms and interactions that occur into the systems are complex and yet to be elucidated. Research and development (R&D) is paramount to understand the physical, chemical, and biological intra-and-interactions (eg. immunological effect, nutrient recycling etc.) of the biofloc system and the environment to better optimize the system or for broader adoption in other fields. For any new system or technology to be adopted, it will require some form of training to the users. This may sometimes be a time-consuming process depending on the social class and/or educational level of the potential users. The majority of Chinese aquaculture firms are concentrated in rural areas with less education. However, this hasn't therefore been an obstacle to the adoption of innovative ways of doing things. This indicates that, even with less-educated potential users of technology, the mode of dissemination of information and demonstration of techniques could ease adoption.

Therefore, for the successful adoption of technologies, three main issues should be addressed (Van Henten 2020): firstly, understanding that the change in technology with a strong skill in CIA and robotics is introducing a new discipline into the technological market. Secondly, being data-intensive, embedding new technology in the future farm's data infrastructure is a challenge on its own. Thirdly, identifying and matching technology to the farmers' needs and training farmers to use more high-tech equipment is crucial and critical success determinants for adopting new technologies.

Prospect of the aquaculture industry

In 2014, the supply of fish directly for human consumption from aquaculture surpassed the capture fisheries for the first time, with anticipation that the aquaculture sector will overtake capture fisheries by 2021 in terms of fish production (FAO 2016; Edwards *et al.* 2019). Historically, fisheries and aquaculture sector has lagged in terms of adoption of efficient information systems. Much attention is now on the opportunities of innovation in information technologies, and how these can change the way fisheries and aquaculture sustainability issues are generated, interpreted and communicated (FAO 2020). Because technology could influence the norms of farming from 'hands-on' and experience-driven management to a data-driven approach, cultural fabric of rural areas and farmers' identity, 'discipline' farmers' work routines in certain ways conditioned by 'algorithmic rationality'. A handful of researchers have outlined that the adoption of technologies can have adverse effects on demand for rural labour and affect marginalized groups such as migrants, in a context of growing separation between labour and capital in agriculture (reviewed in ref. Klerkx *et al.* 2019). Despite the above effects, the authors did not frown upon the adoption of innovative technologies. Of course, there are accompanying trade-offs in any transition or adoption of new technologies that need to be considered. The adoption of technologies seems to uplift all other trade-offs. Other authors also argued that digital technologies could be merged with existing practices to create a combination of 'digital' and 'analogue' skills or give rise to a new 'responsible professionalism' (Blok & Gremmen 2018; Burton & Riley 2018). Concisely, the current aquaculture operations hugely rely on manual labour, including data extraction and processing. The issue of manual information extraction from farm data has been a cause for concern as it impedes real-time decision-making processes in larger farm operations. Therefore, good data-driven farm management techniques are essential for effective farm management.

Given these, we have established a general understanding that for the aquaculture industries to thrive in today's fast-growing techno-centric world, constant improvements are needed for sustainable farm management, from the adoption of advanced production methods to blockchain technologies for traceability in transactions. These improvements largely depend on innovative technologies to provide aquaculture operations with less human labour, effective maintenance, increase productivity, reduce losses through disease, etc. Besides, the health of fish is also essential in determining the success of an aquaculture farm. In a typical fish farm, factors such as farm management, fish husbandry, the activity of fish, climate, pollution, etc. affect the health of a fish.

Conclusion

With the current population growth, technological development has become crucial in the aquaculture industry to protect wild fish stocks, control fish prices and increase productivity. As a surge in population pushes up fish prices due to an increase in demand and shortage of seafood, increasing pressure on wild fish stocks. R&D on technology could mitigate the depletion of wild fish stocks, improve social welfare and alleviate poverty. While the profound impacts of current information technological advancements on aquaculture are being realized, there still remains much potential in this sector compared to the much wider adoption of IT in agriculture and manufacturing industries. We however, anticipate that, with the continuous adaption of information technology, the rate of growth of the aquaculture industry will increase significantly. In brief, the future development of the aquaculture industry largely depends on innovative techniques and should be given due consideration in all ramifications.

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Data availability statement

Data sharing not applicable to this article as no datasets were generated or analysed during the current study

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