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# Artificial Intelligence Approach to Predicting River Water Quality: A Review

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## Abstract

Precise prediction of the water quality time series may provide directions for early warning of water pollution and help policymakers to manage water resources more effectively. This prediction may reveal the proclivity of the characteristic water quality according to the most recent water quality, shifting, and transformation rule of the pollutant in the watershed. The predictive capability of traditional models is constrained due to variability, complexity, uncertainty, inaccuracy, non-stationary, and the non-linear interactions of the water quality parameters. Since the middle of the 20th century, Artificial Intelligence (AI) approaches have been found efficient in bridging gaps, simulating, complementing deficiencies, and improving the precision of the predictive models in terms of multiple evaluation measures for better planning, design, deployment, and handling of multiple engineering systems. This article discusses the state-of-the-art implementation of AI in water quality prediction, the type of AI approaches, the techniques adopted include the knowledge-based system as well as literature and their potential future implementation in water quality modelling and prediction. The study also discusses and presents several possibilities for future research.

**Keywords:** Water quality simulation; Artificial Intelligence; Knowledge-based system; Review

## 1 Introduction

Chemical, physical, and biological properties found in water are generally referred to as the quality of water (1). Accurate evaluation of water quality using the Water Quality Management program is important if decision-makers are to understand, interpret, and use these data to support resource management practices (2,3). Modelling of water quality parameters is an essential part of every water systems analysis. In order to properly manage the watershed, it is necessary to predict the quality of surface water so that appropriate measurements can be taken to avoid pollution from the permissible concentrations. Ideal management of water resources is based on accurate and reliable estimates of future changes (1,4–6).

QUAL2E, Water Quality Analysis Simulation, and the U.S. Army Corps of Engineers Hydrological Engineering Center-5Q are several models commonly applied to water quality management (7). These models, however, are not only time consuming and expensive, but also lack user-friendliness and effective knowledge transfer in model interpretation. Therefore, more models, which do not suffer from these problems, are needed to be developed (8,9). Several scientists noted that the prediction of water quality is impacted by various variables that have parameter-wide nonlinear relationships with each other. Conventional data processing cannot address this significant limitation (10–12). Nonlinear Artificial Intelligence (AI) models, on the other hand, play a significant role in simulating complex and nonlinear processes (13). This situation creates a big gap between model designers and professionals. Selecting a suitable numerical model is a challenging task for novice application users. The forecast precision of traditional models is restricted due to the uncertainty, unpredictability, obscurity, and inaccuracy of water quality information. Progress in AI technology has made it possible over the past decade to apply the developments in computational modelling systems to bridge the gap, as mentioned above (8).

AI methods are currently capable of mimicking this behaviour (14), complementing the defect, and improving the precision of forecast models in terms of multiple assessment measures for better planning, design, operation, and management of distinct engineering systems (15, 16). The significant contributions of the present review article are 1) to categorise AI methods comprehensively and 2) to discuss their advanced application to water quality modelling and prediction.

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## 2 Artificial Intelligence-Based Model for River Water Quality Simulation

The 1956 Dartmouth Conference was held at a time when AI earned its name, purpose, and first accomplishments; it was widely recognised as the birth of AI. Across various fields, the AI field is currently playing an important role, focusing on machines with a human-like mind (17). By incorporating descriptive understanding, procedural knowledge, and reasoning, AI methods enable researchers to simulate human knowledge in clearly defined domains. In addition, advances in AI techniques have enabled the creation of intelligent management systems through the use of shells under established platforms such as MathLab, Visual Basic, and C++. (8, 18).

Recently, AI has achieved significant progress in multiple programs such as autonomous driving, big data, information processing, smart search, image understanding, automatic software development, robotics, and human-computer games, which will have a significant effect on human society. Some of the most important AI-based algorithms include artificial neural networks (ANNs), support vector machine (SVM), random forest (RF), genetic algorithm (GA), enhanced regression tree (ERT), simulated annealing (SA), imperialist competitive algorithm (ICA), and decision tree (DT). AI methods are also associated with experimental design (e.g., response surface methodology, and standardised design) to improve the precision of the optimal solution prediction (19). Advances in data science and data mining techniques such as neural networks (NNs), supporting vector machines (SVMs), and k-nearest neighbours (k-NN) have helped to solve some complicated high-dimensional issues in river water quality prediction (Figure 1).

Over the past two decades, river water pollutants have been considered as one of the global issues that need the full attention of environmental scientists. River water quality, however, is one of the main characteristics to which environmental scholars need to pay full attention. In all developing countries, water quality is a growing concern. Water abstraction mechanisms of domestic use, farming, mining, energy generation, and forestry practices may lead to a decline of water quality and quantity, which affects not only aquatic ecosystems but also the allocation of safe water for human consumptives (20). Thus, the assessment of surface water quality is important in the management of water resources and is very important in monitoring the concentration of pollutants in rivers. Monitoring water quality is costly because pollution control and efficient water resource management require large quantities of data (21). Therefore, AI can be recommended as an alternative technique with high prediction accuracy for predicting the river water quality. AI benefits from traditional techniques since they take account of the non-linear relationship between influential variables and reduce the complexity required to obtain experimental equations (20).

The overall concept behind AI techniques is to explore hidden interactions in large quantities of information and to create models that represent physical procedures governing the system being studied. A model derived from data reflects a correlation between variables of input and output. Such a model can be extremely precise because it conveys all kinds of interactions expressed in the information, including fundamental physics and chemistry (9). Some studies (6, 11, 22-27) that explored river water quality modelling issues using AI methods have revealed encouraging outcomes in recent decades (Table 1).

Several researchers have attempted to predict water quality parameters using AI-based models such as ANN, SVM, and k-NN. In these studies, ANN has been frequently found a stronger predictive model compared to conventional modelling techniques. In the case of 47 sources (2007-2019) reviewed, ANN, SVM, and k-NN have been used in 38, 10, and 1 source, respectively. ANN has been widely used between 2007 and 2015, but from 2015 to 2019, ANFIS and SVM have surpassed ANN, as more recent approaches of AI. Some studies made a comparison between the models.

The study found that different parameters are needed to be used in water quality assessments using various techniques. Different output parameters predictions have been studied, but the ten most important parameters are DO, BOD, TSS, Total Nitrogen, temperature, COD, turbidity, Total Phosphate, $NH_3$, and WQI. The monthly water quality data have been used most in many of these studies to simulate water quality parameters [4, 5, 10, 11, 16-28], which was followed by daily water quality data (3, 25, 35-40).

## 3 Artificial Neural Network Modelling in River Water Quality Monitoring

The theory of artificial neurons was first launched in 1943, with the implementation of the back-propagation practice (BP) algorithm for feedforward ANNs in 1986 (23). ANN is a recent method with a versatile mathematical structure that can identify complicated non-linear interactions between input and output information compared to other traditional modelling approaches (1, 25).

ANNs are common instruments applicable to modeling extremely complex relations, processes, and phenomena. ANNs have been also widely used to predict water quality variables to address contaminant source uncertainty and nonlinearity of water quality data. Nevertheless, the issue with the initial weight parameter and the unbalanced training data set makes it hard to determine the optimal outcomes and hinders ANN modeling efficiency (25). ANN consists of very basic processors called neurons that are strongly interconnected and act together to solve a problem (41). A neuron is an information processing unit, essential for the functioning of the NN; it comprises weight and activation.

From 2007 to 2019, eight types of ANN were applied by different researchers to the prediction of river water quality, namely Back Propagation NN (BPNN), Wavelet NN, Generalized Regression NN (GRNN), Radial Basic NN (RBNN), Feed Forward NN (FFNN), Multi-layer Perceptron NN (MLPNN), Multi-layer Feed Forward NN (MLFFNN) and Adaptive Network-Based Fuzzy Inference System (ANFIS). Among them, five most widely-used models MLPNN (10), RBNN (6), FNNN (5), ANFIS (5), and MLFFNN (4).

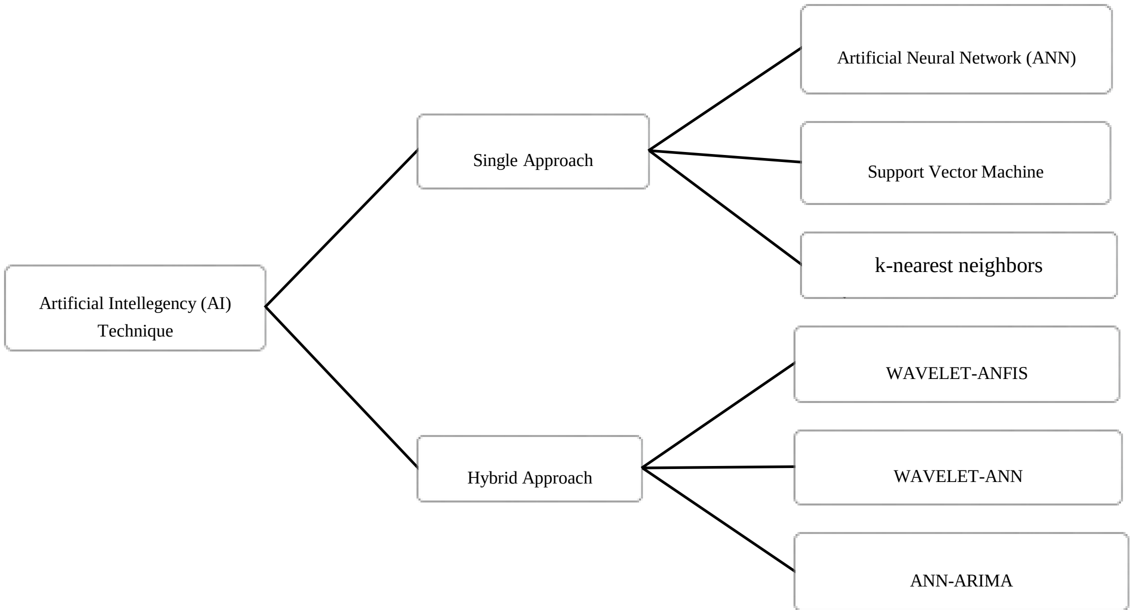


Figure 1: Classification Tree of AI Techniques Applied in Literature to River Water Quality

Several indicators often used to evaluate the ANN model's performance are as follow: Coefficient of correlation (R) between the values observed and the expected values, the mean square error (which can be used to calculate how well the network output corresponds to the expected output), mean absolute error (MAE), root mean square error (RMSE); Coefficient of efficiency (CE), Mean absolute prediction error (MAPE) (which usually expresses accuracy as a percentage), interquartile range (IQR) (which refers to difference between the $25^{th}$ and $75^{th}$ percentile and is used to calculate the entire bias error between the means of the ensemble and the values observed), Nash-Sutcliffe coefficient (NSC), and Determination coefficient (DC) (Table. 2).

The fundamental MLPNN model has three layers: (i) input layer, (ii) hidden layer, and (iii) output layer. The input layer supplies the input data set, the hidden layer processes the features, and finally, the output layer shows the expected results. As can be seen in Table 2, MLPNN is widely used to predict the DO parameters. (15, 28, 31, 32). Moreover, MLPNN is used to predict BOD, COD, EC, TDS, turbidity, and WQI. In predicting the DO parameters, different inputs are used. However, Olyaie *et al*. in 2017 and Ay and Kişi in 2017 both used pH, EC, temperature, and flow as input parameters (15,31). The difference is that Olyaie *et al*. used daily data of seven years, while Ay and Kişi used monthly data of 15 years. Regarding the performance, Olyaie *et al*. obtained $R^2 = 0.955$ and root mean square error (RMSE) = 0.594, while Ay and Kişi obtained $R^2 = 0.98$ and RMSE = 0.52. The time scale of the data does not seem to have any impact on outcomes.

Radial basis function neural network (RBFNN) is a type of NN applicable to general purposes and to various problems. The RBFNN model is more advantageous than other types of NN that have a grouping phase during training, where the hidden node's central location is calculated (36). RBFNN was developed as one of the most common three-layer neural feedforward networks (42) to determine parameters of water quality. This model has a simplified architecture of two weight layers with basic function parameters in the first layer, while the second layer contains linear combinations of those basic functions for the processing of the output and also contains parameters for water quality (1). Some researchers have predicted DO, COD, TDS, $NH_3$-N, Turbidity, and WQI using RBFNN. Cobaner *et al*. in 2009 used GRNN, MLP, and RBNN to forecast SS. Their results confirmed that RBNN performed slightly better than the others (37). In addition, Ahmed (2017) compared some models regarding the DO prediction, which again showed the superiority of the RBNN's performance over the rivals (33).

FFNN propagates the data linearly from input to output; in many practical applications, they are the most popular and widely-used models (43). FFNN is used to predict DO, BOD, TN, and temperature. Four scientists implemented monthly data in FFNN to predict DO using different input parameters (11, 13, 33, 43). Ahmed in 2017 predicted DO using BOD and COD parameters as input, and obtained R = 0.936 and RMSE = 0.709. Ranković *et al*. in 2010 used FFNN to check its capability to predict DO. They added more variables of water quality. Their findings showed that pH and the water temperature are the most powerful variables in DO prediction. In (44), ANFIS was used to learn neural network algorithms and fuzzy logic was used to construct a non-linear mapping between inputs and outputs. Ahmed *et al.* (2017) and Khaled *et al.* (2018) conducted a study into BOD prediction using ANFIS, and they suggested that the ANFIS technique could be successfully applied to building models for predicting the river water quality (34, 55). Elkiran *et al*. (2018) attempted to predict DO at Yamuna River using ANFIS, FFN, and MLR. They found that even both FFNN and ANFIS were found capable of handling nonlinear interactions, the ANFIS model performed better than FFNN (13). The most predicted parameters for ANN are done, DO, BOD, COD and WQI, respectively 13, 5, 5, and 4 studies. And so far, for certain output parameters from certain inputs, each NN type has achieved good results.

Table 1: Artificial Intelligence-Based Models Applied to Water Quality Prediction

| Type of Approach | Methods | Output Parameter | River | Authors |
|---|---|---|---|---|
| Artificial Neural Network (ANN) | Back Propagation neural networks | COD, DO, $NH_3$, Sediment | Dahan River, Taiwan; Jishan Lake, China; River Suktel, India; Yuqiao reservoir in Tianjin | Zhao et al. (2007); Xu and Liu (2013); Chang et al. (2015); Ghose and Samantaray (2018) |
| | Wavelet Neural Network | DO | Jishan Lake, China | Xu and Liu (2013) |
| | Generalized Regression NN | COD | Cark Creek, Turkey | Ay and Kisi (2014) |
| | Radial Basic Neural Networks | COD, DO, $NH_3$, TDS, Turbidity, Suspended sediment | Surma River, Bangladesh; Yangtze River, China; Johor River, Malaysia; Cark Creek, Turkey; Kopili River, India | Ahmed (2017); Basis et al. (2014); Najah et al. (2013); Ay and Kisi (2014); Kumar et al. (2016) |
| | Feed Forward Neural Network | BOD, DO, Total Nitrogen, Temperature, WQI | Gomti river, India; Melen River, Turkey; Surma River, Bangladesh; 59 rivers in Japan; Kinta River, Malaysia; Yamuna River | Singh et al. (2009); Dogan et al. (2009); Ahmed (2017); He et al. (2011); Gazzaz et al. (2012); Elkiran et al. (2018) |
| | Multi-layer Perceptron Neural Networks | WQI, DO, BOD, COD, TDS, Turbidity, Electrical conductivity | Johor River, Malaysia; Heihe River, China; Cark Creek, Turkey; Langat River, Malaysia; Aji-Chay River, Iran | Najah et al. (2011; 2013); Gazzaz et al. (2012); Wen et al. (2013); Ay and Kişi (2014, 2017); Raheli et al. (2017); Keshtegar and Heddam (2018); Zhang et al. (2019); Barzegar et al. (2016) |
| | Multi-layer Feed Forward Neural Networks | BOD, DO, pH Temperature, Turbidity, TN, TP, Boron | Melen River, Turkey; Nakdong River, South Korean; Buyuk Menderes River, Turkey | Dogan et al. (2009); Kim and Seo (2015); Ömer Faruk (2010) |
| | Adaptive Network-Based Fuzzy Inference System (ANFIS) | $BOD_5$ | Yangtze River, China; Beas River, Hong Kong; Surma River, Bangladesh; Aji-Chay River, Iran; Ouizert Reservoir, Algeria; Yamuna River | Deng et al. (2015); Barzegar et al. (2016); Ahmed and Shah (2017); Khaled et al. (2018); Elkiran et al. (2018) |
| Support Vector Machine (SVM) | | DO, BOD, COD, $COD_{Mn}$, $NH_3$–N, $BOD_5$ | Johor River, Malaysia; Weihe River, China; Sefidrood River, Iran; Yamuna River, India; Changle River, China; Kopili River, India; Wen-Rui Tang River, China; Small Prespa Lake, Macedonia, Greece; Pond at Dongying city, China | Najah et al. (2011); Wang et al. (2011); Noori et al. (2012); Liu and Lu (2014); Kisi and Parmar (2016); Kumar et al. (2016); Ji et al. (2017); Li et al. (2018); Fijani et al. (2019) |
| k-nearest neighbors | | TDS, EC | Lighvan Chay River, Iran | Sattari et al. (2016) |
| ANN-ARIMA | | DO, temperature, NH3-N, Boron | Yangtze River, China; Buyuk Menderes River, Turkey | Ömer Faruk, (2010); Basis et al. (2014) |
| Wavelet-ANFIS | | TDS, EC, Turbidity | Johor River, Malaysia; Aji-Chay River, Iran | Najah et al. (2012); Barzegar et al. (2016) |
| Wavelet-ANN | | EC | Aji-Chay River, Iran | Barzegar et al. (2016) |

Table 2: ANN Application to DO Prediction

| Methods | Input Parameter | Output Parameter | Evaluation Criteria | Time Scale Data | Authors |
|---|---|---|---|---|---|
| FFNN | pH, total alkalinity, total hardness, total solids, COD, DO, BOD, $NH_4$-N, $NO_3$-N, Cl, $PO_4$, K, and Na | BOD and DO | $R^2$, RMSE, and bias computed | Monthly (10 years) | Singh et al. (2009) |
| FFNN | pH, T, chloride, total phosphate, nitrites, nitrates, ammonia, iron, manganese, and EC | DO | R, MAE, and MSE | Monthly (1 year) | Ranković et al. (2010) |
| FFNN and ANFIS | DO, BOD, pH, and T | DO | RMSE, MSE, and DC | Daily (1999-2012) | Elkiran et al. (2018) |
| FFNN and RBFNN | BOD and COD | DO | R, MSE, and coefficient of efficiency (E) | Monthly (2010-2012) | Ahmed (2017) |
| MLFFNN | T, boron, and DO | temperature, boron, and DO | R. RMSE, MAPE, and NSC | Monthly (8 years) | Ömer Faruk, (2010) |
| MLFFNN | pH, DO, turbidity, TN, and TP | pH, DO, turbidity, TN, and TP | $R^2$, RMSE, and IQR | Daily (2009-2012) | Kim and Seo (2015) |
| MLPNN | pH, EC, $Cl^-$, $Ca^{2+}$, total alkalinity, total hardness, $NO_3$-N, and $NH_4$-N | DO | R, RMSE, and MSE | Monthly (6 years) | Wen et al. (2013) |
| MLPNN | COD, PO4, TS, K, Na, Cl, EC, pH, and $NH_4$-N | BOD and DO | R, RMSE, %RMSE, and Willmott's index of agreement | Monthly (2001-2010) | Raheli et al. (2017) |
| MLPNN | pH, EC, T, and river discharge (Q) | DO | RMSE, Nashe Sutcliffe efficiency coefficient (NSC), MARE and, R | Daily (July 2007-Jan 2014) | Olyaie et al. (2017) |
| MLPNN | pH, EC, T, river discharge (Q), and DO | DO | RMSE, MAE, and $R^2$ | Monthly (1996-2010) | Ay and Kişi (2017) |
| RBFNN | DO and $NH_3$-N | DO and $NH_3$-N | R, MAP, and RMSE | Weekly (2005-2014) | Basis et al. (2014) |

## 4 Support Vector Machine Approach in River Water Quality Monitoring

SVM has raised expectations in recent years since it has been successful in the context of classification problems, regression, and prediction; for example in machine learning concepts and methods, statistics, statistical analysis, and convex optimization (57). Several previously-conducted studies have confirmed the high potential and outstanding performance of SVM. This level of effectiveness is largely due to the concept of structural risk minimization (SRM) in SVM, which is more generalized and superior to the theory of empirical risk minimization (ERM), when applied to neural networks (24).

The results of this study are in line with those of the study conducted by Chen (2010) who claimed that the concept of SRM in SVM, which is focused on the theory of statistical learning, may successfully resolve the Neural Network deficiency (58). SVMs are able to produce reliable and stable classification tests even if the input data are neither monotonous nor linearly separable. They can quickly determine more relevant information. A key feature of SVM is that during the training process, it automatically defines and integrates support vectors and avoids the control of non-supporting vectors over the configuration; this means that the model can handle noisy conditions well (59). SVM has the ability to track events in the past with some primary actual training vectors incorporated in the models as support vectors to improve future predictions through learning from past experience. On the other hand, SVMs have some disadvantages. Because of the inherent complexity of mapping non-linear input spaces to high-dimensional character-spaces and the extrapolation of models, it is not easy to understand and interpret the behavior of nonlinear SVM models. Moreover, the model is entirely dependent on records when data inconsistencies occur (57). In several studies, SVM has been successfully applied to water quality prediction in case of BOD (56, 60), DO (40, 53), COD (30), Total Phosphate, and Total Nitrogen (53).

## 5 Hybrid Approach to River Water Quality Monitoring

Due to the robustness and accuracy of wavelet-AI models, their application to hydrology has gradually increased in recent years. The success of this model is attributable to the efficiency of multi-resolution processing wavelet transformations, the identification of noise and edge effects via a signal, and the high capability of AI in dealing with optimization and prediction problems (4). Some researchers have investigated a number of hybrid models in terms of water quality prediction. Their results have shown that high-vanishing wavelets could help improve the robustness and efficiency of hybridized wavelet-AI models. The performance of these hybrid models was compared to wavelet models. Najah *et al*. (2012) used the integrated wavelet-ANFIS model to predict monthly water TDS, EC, and turbidity. They found the greatest accuracy level obtained by making the fifth cross-validation length of data records. Additionally, they confirmed the superiority of the wavelet-ANFIS model compared to ANFIS model in terms of prediction accuracy (16). It can be inferred that wavelets with long vanishing times can be useful for improving the quality and reliability of wavelet-AI hybrid models. The wavelet-ANFIS model has been also found more successful than the ANN wavelet model in terms of EC prediction (12).

## 6 Evaluation and Assessment

After ANNs and (chronologically) fuzzy theory, the largest development in hydrological parameters is SVM. In most literature reviews, conventional predictive regression models have been found ineffective compared to AI-based models such as ANN, ANFIS, and SVM. Although ANN is vulnerable to the hidden nodes number, the SVM is responsive to the selection of mapping kernels, which means the optimization of these variables will achieve comparable results with both models. In the latest studies conducted in this field, ANN has been the most popular technique.

## 7 Recommendation for Future Research

Another promising strategy in AI development is the hybrid combination of two or more of the above techniques to create a further flexible modelling scheme for water quality. Moreover, progress in AI is made in two fields in parallel: fundamental tool capabilities and actual implementations in solving water quality issues. Research is presently ongoing to develop better AI instruments that can provide better representational knowledge systems, alternative analysis methods, and alternate processes to address uncertain or insufficient information. The use of database management systems, visual displays, and knowledge improvement modules can improve the precision of existing modelling systems worldwide. In this context, with simulation systems evolving, the criteria for better AI software will be increased, which in turn may lead to better AI technology implementation strategies. Most notably, simulation systems must step out from the laboratory and onto real practice. Continued research will develop AI technology and its implementation in the simulation of water quality.

## 8 Conclusion

Current models applied to water quality prediction are not user-friendly enough and mostly their implementation is subjected to substantial restrictions. Selecting a suitable numerical model is a challenging task for novice application users. The incorporation of current heuristic understanding of model manipulation and the intellectual manipulation of calibration parameters are therefore instrumental. The latest developments in AI technology provide a way of filling the gap between the designer and the model professional. This article examined the state-of-the-art models proposed for water quality prediction and the progress made in integrating AI into these models. The ANN method can contribute distinctly to the embedded model.This approach can help novice users to assess whether digital models produced by function modelling are actual phenomena. Several plans for the future are investigated and submitted for further advancement and their potential. More progress in function modeling in this direction is expected to be promising with the ever-increasing potential of AI technologies.

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## Ethical issue

Authors are aware of, and comply with, best practice in publication ethics specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests and compliance with policies on research ethics. Authors adhere to publication requirements that submitted work is original and has not been published elsewhere in any language.

## Competing interests

The authors declare that there is no conflict of interest that would prejudice the impartiality of this scientific work.

## Authors’ contribution

All authors of this study have a complete contribution for data collection, data analyses.

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