JESEH

Journal of Education in Science, Environment and Health

Volume: 11 Issue: 2 Year: 2025

ISSN: 2149-214X

Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025 e-ISSN:2149-214X

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JESEH
Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025
e-ISSN:2149-214X

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JESEH Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025 https://doi.org/10.55549/jeseh.796

Use of Artificial Neural Network in Educational Laboratory Applications: Low-Velocity Impact Test

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Article Info

Article History

Published:
01 April 2025

Received:
03 January 2025

Accepted:
10 March 2025

Keywords

Educational applications
Artificial neural network
Aramid composite plates
Low-velocity impact

Abstract

In this study, which focuses on selecting the material and predicting its mechanical behaviors in materials science, an Artificial Neural Network (ANN) was used to predict and simulate the low-speed impact effects of hybrid nano-doped aramid composites. There are not enough studies about open education practices in this field. Since error values below 1% were obtained with the proposed method, it has been shown that ANN results contribute to the prediction and derivation of force-time, force-displacement, and energy-time curves. It was concluded that the proposed ANN model could be useful in finding solutions to the impact responses of nanohybrid-doped aramid composites. ANN successfully predicted the prediction process for Part I and Part II, with accuracy rates of 99.4% and 99.3% for the displacement feature, 99.2% and 99.1% for the energy feature, and 97.1% and 98.3% for the force feature, respectively. This study is an applied training step that will simulate the impact strength of composite materials reinforced with nano additives and make serious contributions to important and easy-to-access technical training with a library feature that can be used as a basis for use as training material.

Introduction

The modern world is going through profound changes, and education has become the key to the development of a nation. With rapid technological development and international cooperation, competition intensifies, and economic globalization accelerates (Lin et al., 2021; Quian et al., 2018). Engineering education is the basis of national development and social development. For manufacturing enterprises to successfully enter the Industry 4.0 era and gain advantages in this new wave of the industrial revolution, they need to use internet thinking to transform manufacturing enterprises and promote the deep integration of informatics and industrialization. Research and management of risks related to the Internet strategic transformation of manufacturing enterprises directly affect the success or failure of the transformation of enterprises. This is also very important in terms of preparing the infrastructure for Industry 5.0. A risk assessment model based on a backpropagation (BP) artificial neural network was created for the Internet strategic transformation of a manufacturing organization, and a case study was conducted on an organization (Honglei et al., 2022).

In the current green environmental pressure, businesses must proactively incorporate competitive issues into their strategic plans to create innovative initiatives and gain a foothold in the highly competitive business world (Abbas, 2020). Universities strive to create an attractive classroom environment by creating a strong impression and directly influencing the perceived teaching quality of faculty members, improving overall performance (Li et al., 2017). The findings revealed that financial incentives, promotions, and performance evaluations had no impact on the faculty member's job performance. The present result is consistent with (Hee et al., 2020). However, this found that financial incentives motivate employees to perform better (Koo et al., 2020). Similarly, it has supported findings in the literature and claims that career development empowers people and promotes a sense of accomplishment, which leads to workplace satisfaction (Benson et al., 2019). Promotion is a great approach for academics to achieve job satisfaction. With the knowledge economy expanding so rapidly, informed decision-making is seen as an important tool for success and prosperity (Yang et al., 2019). To save university students from these and many similar psychological problems, digital materials, and analysis methods need to be used more widely in education and application environments. Professional behavior can be improved with the right resources available in academic environments. Here, the fact that the educational environments are interesting and business-oriented will increase the respect for the instructor and both parties will work happily and productively in a more productive educational environment. For this, educational environments need to be prepared for business life and digital content production must be supported.

Artificial intelligence technology has begun to be used in many areas of life. A person with high self-esteem is one who has better socio-emotional and cognitive functions in business life (Harun, 2017; Silverthorn, 2017). Low self-esteem appears to be associated with poor emotional adjustment in personal and social domains (Zhao et al., 2022). Therefore, teaching methods of cognitive problem-solving strategies help students improve their self-esteem (Silverthorn, 2017). Nowadays, the use of simulation-based educational materials is becoming increasingly important in the field of applied sciences, especially in complex or risky experiments that cannot be performed in laboratory environments, by taking advantage of developing technology. Simulations are radically changing educational practice in science and technology. Artificial intelligence technologies have facilitated access to data and information that were previously difficult to obtain in experimental studies in science and engineering. However, experimental studies performed in laboratory environments can be costly and time-consuming. These difficulties reveal the importance of simulations in applied training. Simulations offer students the opportunity to experiment and understand complex concepts in a digital environment.

Accessibility means the ability to use any system or service that has been developed. In education, accessibility aims especially for individuals with disabilities to access educational materials and learning experiences easily. Open education means that learning resources and materials are freely accessible and shareable online (Adedoyin et al., 2023). Open education practices aim to ensure that everyone can access educational resources beyond traditional education. Today, artificial intelligence plays an important role in the field of education. This technology provides students with a more customized and effective learning experience (Ahmad et al., 2022). Artificial intelligence can recommend personalized learning materials to students by analyzing students' performance and learning styles. Using artificial intelligence methods, various tools and applications can be developed to increase accessibility for individuals with disabilities. For example, a better access environment can be provided to visually impaired students with some solutions such as audiobooks, speech recognition systems, or text-to-speech applications. Artificial intelligence tracks students' educational progress, helping them understand their strengths and weaknesses. Thus, it can also improve the learning process applied to students. Artificial intelligence can also promote cultural diversity and international cooperation by translating educational materials into different languages (Cantú-Ortiz et al., 2020). This technology can adapt educational materials to the needs of individuals with disabilities. For example, it can add subtitles for hearing-impaired students or make special color adjustments for colorblind students. When used in accessibility and open education applications, artificial intelligence can make education more inclusive and accessible. Thus, it can help every individual have equal access to educational opportunities.

This study aims to develop professional skills and abilities during and after university education and to find solutions to employment problems. Using modern technology and science to master students' basic socio-psychological pressure situations and analyze students' problems is the developing trend of the age. Secondly, practical deficiencies in scientific education stand out when looking at university students in terms of applied digital education factors. This study aims to outperform traditional application methods by developing an application-based ANN model to analyze current university vocational education and university students' work-life stress, and the data-matching results are successful. This study aims to predict and simulate the low-velocity impact effects of CNT and ZrO_2 reinforced aramid composite plates to predict the mechanical behavior of the material and systematic material selection in Material Analysis and Material Selection courses using the ANN method. Thus, to provide students with comprehensive educational material about material selection criteria. Thanks to the use of ANN, predicting the low-velocity impact responses of aramid composite materials with different nano-doping ratios is now more efficient and economical. This study aims to transform the practice of mechanical and materials engineering by highlighting the potential to obtain more precise and accurate results in industrial and academic fields such as material architecture and strength analysis.

Method

Mechanical Experiments

In this study, several mechanical experiments were carried out to obtain data for ANN predictions. Aramid composites are preferred materials in various industrial applications due to their high strength and lightness. However, their behavior can become complex when subjected to impact loads. This situation is determined by analyzing the data obtained because of detailed and costly mechanical experiments. For these experiments, Kevlar 29 CT736 ballistic para-aramid 410 g/m^2 density fabric reinforcement material and vinylester Polives 701 matrix were used. MWCNT and ZrO_2 were used as hybrid nano additives. MWCNT and ZrO_2 reinforcement nano additives were added into the vinylester resin at determined rates, dispersed mechanically and then in an ultrasonic mixer, then applied on a 6-layer aramid fiber fabric and placed in a vacuum environment. Then, according to the resin curing instructions, it was cured with a hot press at 70℃ under 5 bar pressure for 2 hours and left to cool naturally. In this way, the material was produced in 2 parts, with a low nano additive ratio (max. 0.5) and high nano additive ratio (max. 1.75), 6 samples for each additive ratio, for a total of 42 samples. The produced composite plate was subjected to impact tests at 10 J and 15 J energy levels and cut with a water jet according to ASTM D-7136 standard for low-speed impact tests. As a result of the tests, maximum force, displacement, and absorbed energy data were obtained.

Mechanical Experiments

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Artificial Neural Networks

ANN is a subfield of machine learning and artificial intelligence created by modeling the functioning of biological neurons. Artificial neural networks are a powerful method used to solve many problems such as data analysis, pattern recognition, classification, and regression. The simplest processing unit in ANN is a single-layer perceptron called a neuron (see Figure 1) (Demuth et al., 2014).

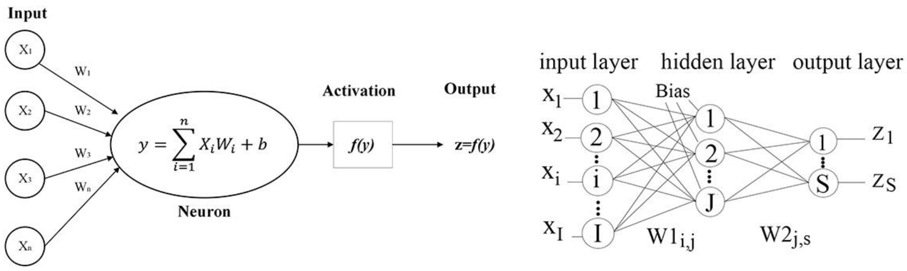

Figure 1. ANN structures

Considering *n* inputs, the linear weighted sum of the inputs of a single neuron is obtained as in Equation 1:

$$y = \sum_{i=1}^{n} X_i W_i + b \quad (1)$$

where X_i is the input value, W_i is the weight value corresponding to the input value, and *b* is the bias value. In this study, a hyperbolic tangent function in the range (-1 to +1) shown in Equation 2 was used as the activation function.

$$f(y) = \tanh(ay) \quad (2)$$

where the value of parameter *a* is 1.5. This parameter corresponds to the Tanh15 activation function, which scales the input values of ANNs by a factor of 1.5 by forcing the range of input upper values to +1 and the range of lower values to -1. This means that the activation function reaches its extremes faster, speeding up the learning rate of an ANN.

The multilayer perceptron, which is a complex and functional model, consists of multiple neurons connected on a layered architecture. The multilayer sensor model works by progressing from the input layer to the output layer, as shown in Figure 1 (Jain et al., 1996). The learning process of ANN occurs by updating the weight values of each neuron using training data and a training algorithm (Cha et al., 2023). The success of the learning process is determined using test and evaluation data. The Mean Square Error function is often used to adjust the values of weights. The Mean Square Error (MSE) function was calculated using Equation 3.

$$MSE = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (T_{ij} - Z_{ij})^2 \quad (3)$$

where Z_{ij} corresponds to the output of the activation function in the ANN, T_{ij} refers to the target values, *n* represents the total number of outputs, and *m* represents the number of training cases.

In this study, 80% of the data set was used for training the ANN, 10% for verification, and 10% for testing. In data selection processes, a randomization algorithm was applied to the data set and very good results were obtained. A splitting procedure was applied to divide the dataset into training and validation. Matlab software was used to develop and validate the ANN method. In the training of the ANN, 4 neurons were used in the input layer, 10 neurons in each of the 2 hidden layers, and 3 neurons in the output layer. An ANN structure with maximum fitness value was obtained by accepting the test coefficient as 0.001, the momentum coefficient as 1, and the learning coefficient as 1. The number of iterations and minimum error rate were accepted in the stopping criteria of the ANN. These values were chosen as the number of iterations as 20000 and the minimum error rate as 0.01. ANN architecture training and validation were obtained using a program that calculates MSE values. The program works by first training the ANN with zero neurons in the hidden layers. Then, for training and validation, the MSE value is calculated, and the neurons are incremented by one. Finally, the MSE is recalculated until the maximum number of neurons is reached according to the size of training cases (T_c) required to train. If the ANN has no hidden layer, the number of training cases required should be more than 2.5 times the number of output weights. If the ANN has a single hidden layer, the required number of training cases should be more than 2.5 times the number of hidden weights. If the ANN has two hidden layers, the required number of training cases should be greater than 2.5 times the number of hidden weights. Depending on the status of the hidden layers in the ANN, T_c is calculated with Equation 4 below.

$$T_c > 2.5[h_1(I+1) + h_2(h_1+1)] \tag{4}$$

where I is the number of neurons in the input layer of the ANN, h_1 is the number of neurons in the first hidden layer, and h_2 is the number of neurons in the second hidden layer. The coefficient of 2.5 in the equation is a parameter obtained through experiments to solve a problem using nonlinear activation functions in neurons. The R^2 coefficient of determination used to evaluate the quality and performance of the ANN model was calculated with Equation 5 below (Sabir et al., 2023).

$$R^2 = 1 - \frac{\sum_{i=1}^{k}\left(Z_i^{predicted} - t_i^{experimental}\right)^2}{\sum_{i=1}^{k}\left(t_i^{experimental} - t^{-experimental}\right)^2} \tag{5}$$

where $t^{experimental}$ corresponds to the forces obtained from experimental tests, $Z^{predicted}$ corresponds to the ANN output predicted by the ANN, $t^{-experimental}$ corresponds to the arithmetic mean of the data contained in the experimental data, and k is the size of both the predicted and experimentally obtained dataset (Zhang et al., 2023). Finally, *RMSE* was also used to calculate the performance of the ANN model and was calculated by Equation 6.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{k}\left(Z_i^{predicted} - t_i^{experimental}\right)^2}{k}} \tag{6}$$

R^2 and *RMSE* calculations were used to evaluate the overall performance of the ANN model (Elhattab et al., 2024). These do not consider error estimates at local points in the data. Therefore, the Absolute Error (AE) specified in Equation 7 was used to evaluate a more detailed local accuracy of the ANN.

$$AE = \left|Z_i^{predicted} - t_i^{experimental}\right| \tag{7}$$

Thereupon, the MAX value was calculated with Equation 8 below.

$$MAX = max\left(\left|Z_i^{predicted} - t_i^{experimental}\right|\right),\ i, \ldots, k \tag{8}$$

AE is used to visualize the error of ANN models in a plot where MAX represents the highest point in the graphs. This serves to graphically observe the evolution and maximum value of the local error.

Results and Discussion

Force-time, energy-time, and force-displacement data under 10 J and 15 J energy levels were used in the graphs obtained from mechanical experiments. The interactions of different ratios of Part I (0-0, 0.5-0.5, 0.5-0, 0-0.5) and Part II (1.75-0, 0-1.75, 1.75-1.75) CNT and ZrO_2 nano additives on the strength of the composite are discussed. Comparisons were made at 10 J and 15 J energy levels, taking the pure sample as a reference. In this study, the input data for the dataset used for training the ANN consists of CNT and ZrO_2 contribution rates, impact force duration *t* (seconds), and impact energy (Joule) values. The output data consists of displacement amount (mm), absorbed energy (Joule), and impact force (Newton) values. The data set used in this study was obtained because of mechanical experimental procedures. These data were used to adjust the weights of the ANN. Comparisons between experimental studies and ANN were made in two groups according to the proportions of additives. The first group was carried out with a low nano additive ratio (max 0.5), and the second group was realized with a high nano additive ratio (max 1.75). The purpose of performing it in two groups here is to test the performance and stability of the developed ANN method according to different contribution rates. For both data pieces (part I and part II), the experimental results and ANN predictions of the displacement feature showed a close distribution to each other. ANN predicted the displacement property with 99.4% accuracy for Part I and 99.3% for Part II. Graphical distributions of experimental and ANN prediction values of displacement values for both parts are shown in Figure 2.

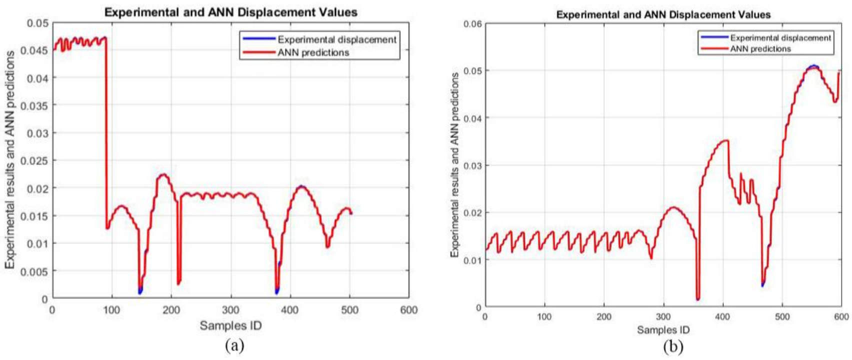

Figure 2. Experimental and ANN displacement values in part 1(a) and part 2(b)

In Part I, the best validation performance value for the displacement feature was obtained as 1.7335e-08 in the 78th period (epoch). In Part II, the best validity performance value was obtained as 2.3224e-08 in the 72nd period (epoch) (see Figure 3).

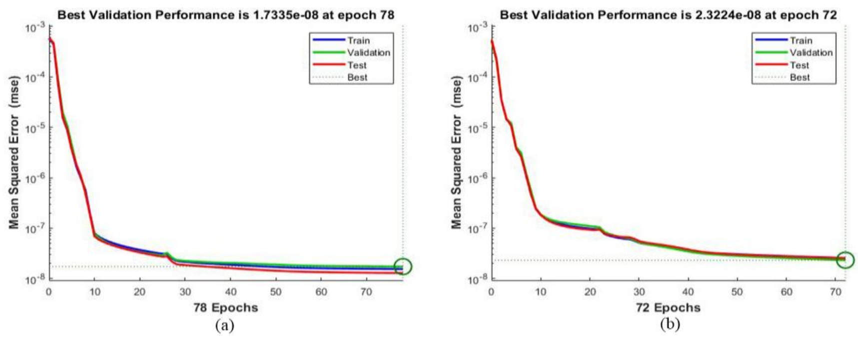

Figure 3. Best validation performance for displacement in part 1(a) and part 2(b)

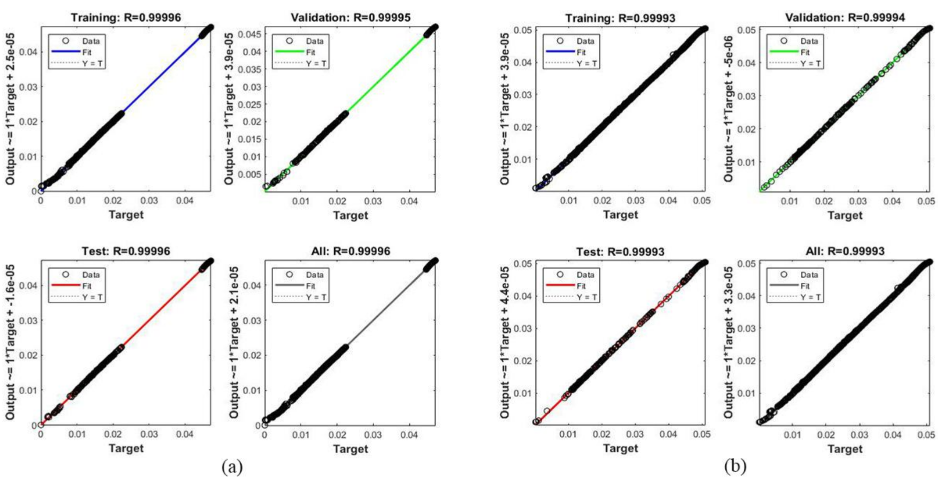

Figure 4. Training, testing, and validation regression graphs for displacement in part 1(a) and part 2(b)

The purpose of regression model estimation is to find the regression line that best represents the relationship between the dependent variable and the predictive variables. It is done to see the harmony between ANN outputs and experimental data and the level of this harmony. In other words, we can see how to approximate the results ANN can produce to the experimental output (Soares dos Santos et al., 2016). The regression (R) value for the training, testing, and validation procedures for the displacement value in Part I was calculated as 0.99996 and in Part II was calculated as 0.99993. This shows that experimental data and ANN predictions match with high accuracy (Figure 4).

Gradient, mu, and validation fail graphs for the displacement feature in Part I and Part II are shown in Figure 5. Here, Mu is the mean of the normal distribution expressed as a scaler value or series of scaler values. The gradient is the slope of the square of the error function concerning unknown weights and biases. Val fail is shown to detect validation errors at each epoch. In Part I, at the 78th epoch, the gradient value was determined as 9.6329e-08, the Mu value was 1e-09, and the validation fail value was 0. In Part II, in the 72nd epoch, the gradient value was determined as 9.8906e-08, the Mu value was 1e-08, and the validation fail value was 0.

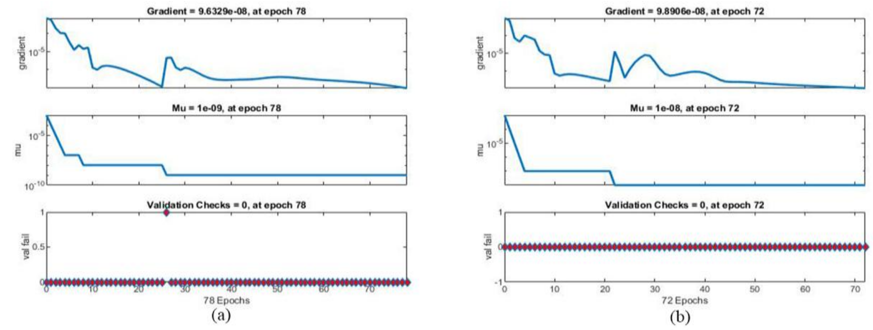

Figure 5. Gradient, mu, and validation fail graphs for displacement in part 1(a) and part 2(b)

For the energy feature, experimental results and ANN predictions showed a close distribution in both Part I and Part II. ANN predicted the energy property with 99.2% accuracy for Part I and 99.1% for Part II. Graphical distributions of experimental and ANN prediction values of displacement values for both parts are shown in Figure 6.

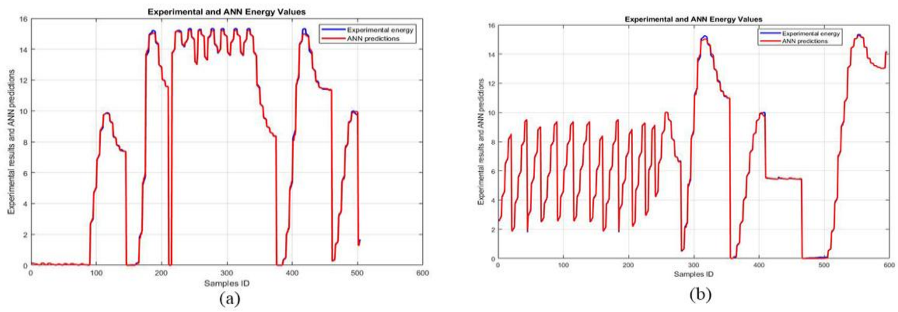

Figure 6. Experimental and ANN energy values in part 1(a) and part 2(b)

The best validation performance value for the energy feature in Part I was determined to be 0.0056 in the 288th epoch. In Part II, the best validity performance value was obtained as 0.0035 in the 316th period (epoch) (Figure 7).

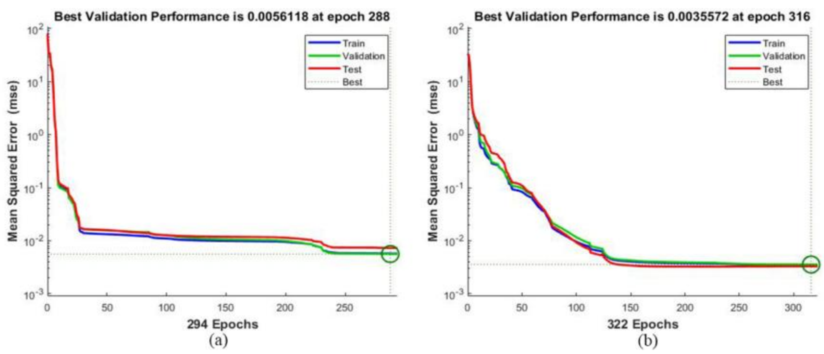

Figure 7. Best validation performance for energy in part 1(a) and part 2(b)

The regression (R) value of the training, testing, and validation processes for the energy feature in Part I was calculated as 0.99992, and in Part II, it was calculated as 0.99991. This shows that experimental data and ANN predictions match with high accuracy (Figure 8).

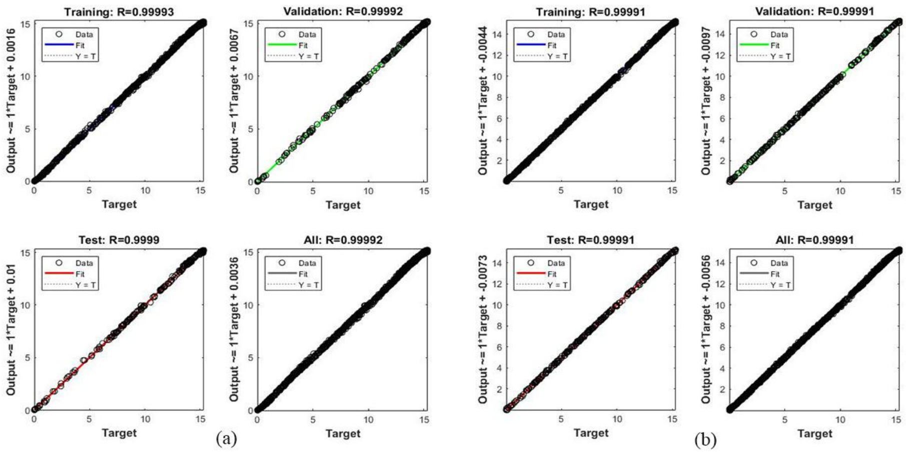

Figure 8. Training, validation, test, and regression graphs for energy in part 1(a) and part 2(b)

Gradient, mu, and validation fail graphs for the energy feature in Part I and Part II are shown in Figure 9. In Part I, at the 294th epoch, the gradient value was calculated as 0.0009, the Mu value was 0.0001, and the validation fail value was 6. In Part II, the gradient value was determined as 0.0005, the Mu value was 1e-05, and the validation fail value was 6 in the 322nd epoch.

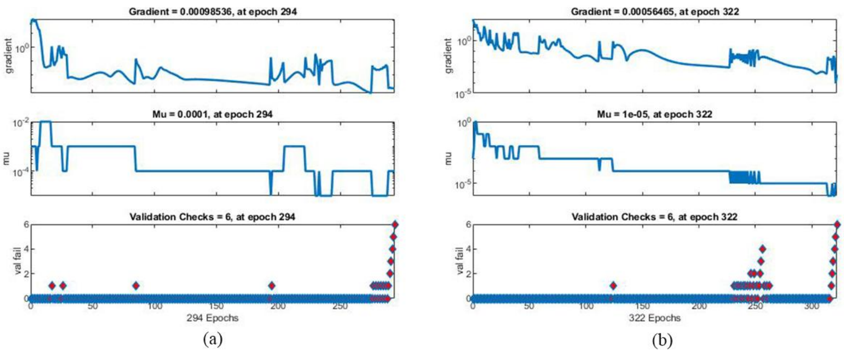

Figure 9. Gradient, mu, and validation fail graphs for energy in part 1(a) and part 2(b)

For the force property, experimental results and ANN predictions showed a close distribution in both Part I and Part II. ANN predicted the force property with an accuracy of 97.1% for Part I and 98.3% for Part II. Graphical distributions of experimental and ANN prediction values of displacement values for both parts are shown in Figure 10.

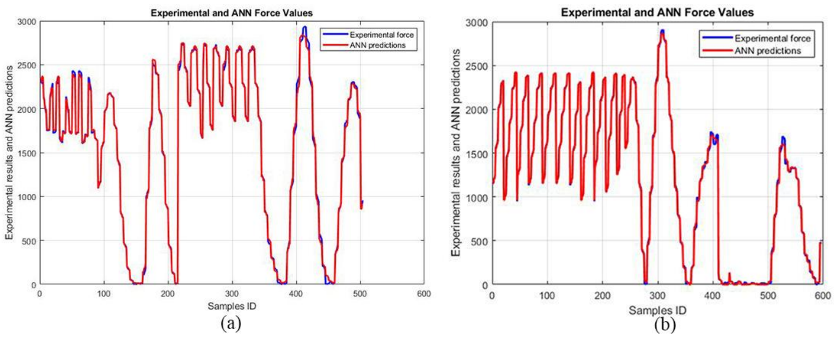

Figure 10. Experimental and ANN force values in part 1(a) and part 2(b)

The best validation performance value for the force feature in Part I was determined as 1113.308 in the 384th period (epoch). In Part II, the best validity performance value was calculated as 370.940 in the 578th epoch (Figure 11).

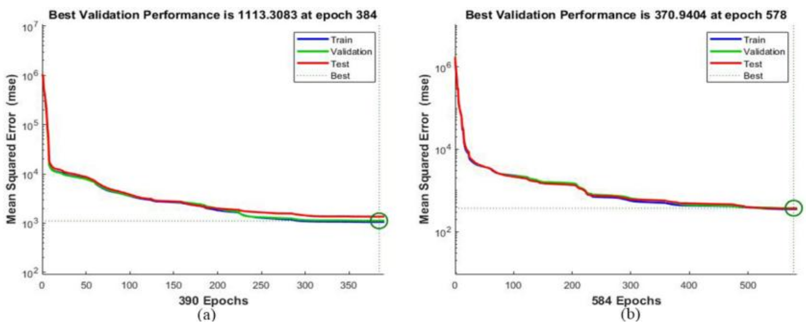

Figure 11. Best validation performance for force in part 1(a) and part 2(b)

The regression (R) value of the training, testing, and validation processes for the force feature in Part I was calculated as 0.99931, and in Part II, it was calculated as 0.99976. This shows that experimental data and ANN predictions match with high accuracy (Figure 12).

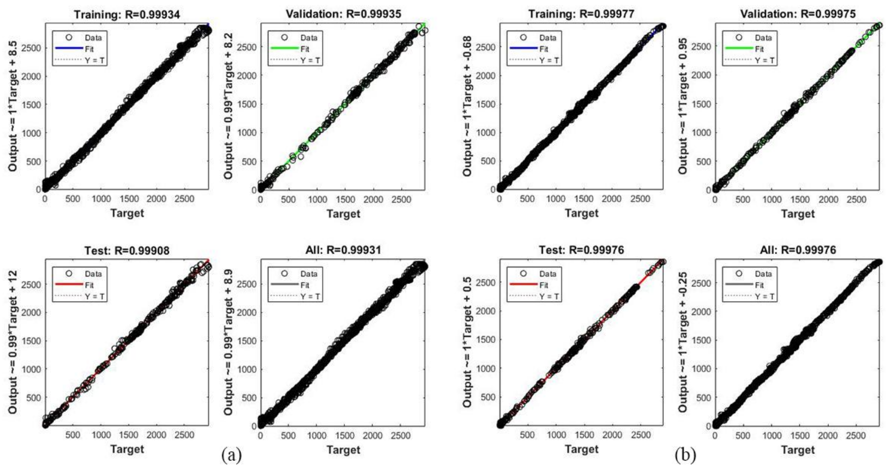

Figure 12. Training, validation, test, and regression graphs for force in part 1(a) and part 2(b)

Gradient, mu, and validation fail graphs for the force feature in Part I and Part II are shown in Figure 13. In Part I, at the 390th epoch, the gradient value was calculated as 345.694, the Mu value was 0.1, and the validation fail value was calculated as 6. In Part II, the gradient value was calculated as 197.152, the Mu value was 0.1, and the validation fail value was 6 in the 584th epoch.

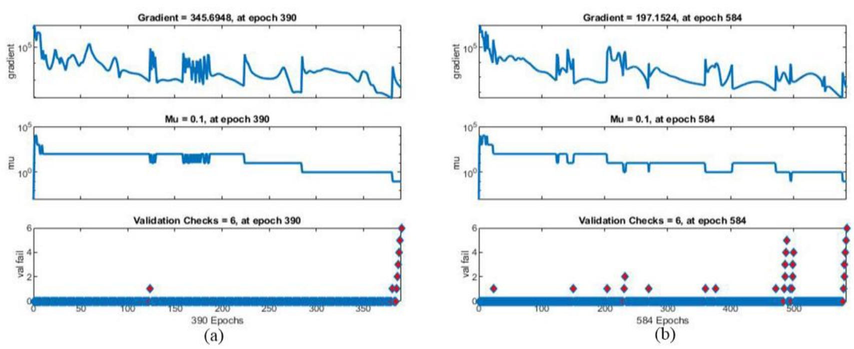

Figure 13. Gradient, mu, and validation fail graphs for force in part 1(a) and part 2(b)

Table 1. Performance values of the ANN model.

Parts	Features	Accuracy	R^2	RMSE	Max
Part I	Displacement	99.4%	0.99996	0.3715	1.1724
	Energy	99.2%	0.99992	0.4325	1.4578
	Force	97.1%	0.99931	0.4756	1.8652
Part II	Displacement	99.3%	0.99993	0.3787	1.1952
	Energy	99.1%	0.99991	0.4432	1.4697
	Force	98.3%	0.99976	0.4893	1.9641

Table 1 shows the accuracy, R^2, RMSE, and MAX performance values of the ANN model for Part I and Part II. In all cases examined, ANN prediction values showed results close to the experimental data. In this study, an educational simulation interface application was created using the developed ANN model, focusing on the need for students to systematically select materials and predict the mechanical behavior of materials in the Material Analysis and Material Selection courses from the Mechanical and Materials Engineering Department course curriculum. The main purpose of this application is to use this ANN-based application developed to provide students with a comprehensive education on material selection and prediction of mechanical behavior. This application especially allows students to gain practical experience and turn their theoretical knowledge into practice. The interface of the developed application is shown in Figure 14.

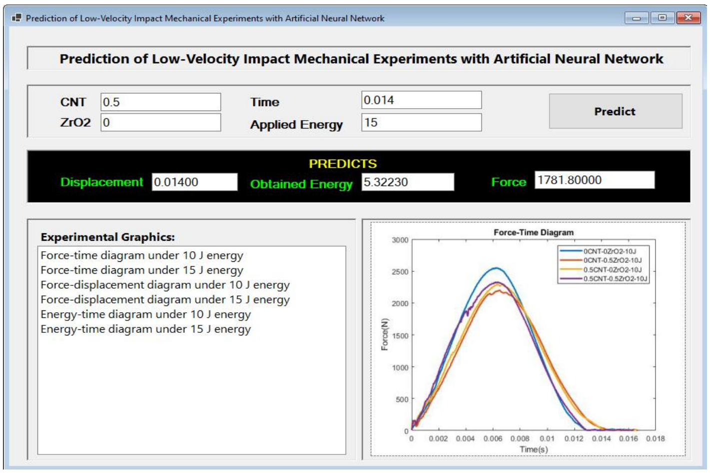

Figure 14. Prediction of low-velocity impact mechanical experiments with ANN

The developed application has an updateable library. By recording the input values entered by the students and their corresponding prediction values, the infrastructure of artificial intelligence studies is being prepared to further develop experiences. The use of ANN can be an effective method for modeling and predicting complex material behavior. It is important to evaluate whether the ANN is effective not only in low-speed impact effects but also in different application areas. For example, the usability of ANN can be investigated in other applications such as high-speed impacts and vibration analysis. Optimizing the training process and prediction time of the ANN model can make it more useful for real-time applications. This can provide faster and more effective solutions in engineering applications. These suggestions and opinions can guide future studies and research on similar topics.

Conclusion

This study provides a solution to the impact responses of nano-hybrid doped aramid composites. The proposed approach makes a significant contribution to the design of composite materials. In this study, the performance of the ANN model developed to predict the low-speed impact effects of nano hybrid-doped aramid composite sheets was examined. Experiments were carried out in two groups with different contribution rates, and the ability of the ANN to adapt to these different conditions was evaluated. A high agreement was observed between the experimental results and ANN predictions for displacement, energy, and force properties. Regression analyses also confirmed these situations. As a result, the developed ANN model successfully predicted the low-speed impact effects of different nano-doped aramid composites. This highlights the applicability of ANN as a reliable tool in engineering applications of such materials. Using this study, especially for support purposes in applied laboratory training materials, will provide students with the opportunity to put their theoretical education into practice more easily and cost-effectively. The specially developed application allows students to understand and analyze the problems they may encounter in the material selection process by using the digital environment more effectively and efficiently. As a result, this study provides students with the ability to predict material behavior and provides a practical application of the ANN approach in Mechanical and Materials Engineering education.

Recommendations

This study will be tried to be developed on different educational topics using different methods.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflicts of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Funding Declaration

The authors did not receive support from any organization for the submitted work.

Acknowledgements or Notes

We would like to thank all units for their support in this study.

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Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025 https://doi.org/10.55549/jeseh.777

Students' Level of Awareness on the Environmental Implications of Generative AI

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Article Info

Article History

Published:
01 April 2025

Received:
02 January 2025

Accepted:
09 March 2025

Keywords

Generative AI
Artificial intelligence
Environmental Education

Abstract

In recent years, the number of studies on artificial intelligence or AI has increased tremendously, and their place in daily life is beginning to be felt more and more each day. Current rise of generative AI tools has brought forth dangers regarding its potential misuse, leading to impacts on the environment. College students were surveyed using an infographic and a 5-point Likert scale to assess their awareness regarding these environmental implications. The students exhibited a lack of awareness on most of the implications, only recognizing generative AI's impact on the environment to a certain extent. In particular, the awareness of students on the environmental implications of generative AI such as its carbon footprint resulted in an unclear consensus. Additionally, students only showed an understanding of the electricity that generative AI demands and not also the fresh water and rare metals it consumes. The data suggests that this lack of awareness may stem from insufficient knowledge regarding generative AI. To address these concerns, further promotion in raising awareness was recommended, and an infographic was proposed.

Introduction

In recent times, artificial intelligence or AI has taken the world by storm and has started to embed itself in our society. AI revolves around digital computers or robots that have the capability to perform tasks that require human intellect. This includes being able to reason, to solve problems, as well as to converse. Shruti (2024) categorizes AI systems by their purpose. It can be trained to be reactive, utilize past information, understand human emotion, or be self-aware. Uppal (2023) instead splits AI systems into two, strong AI and weak AI. Strong AI refers to systems designed to exhibit human-like tendencies and intelligence while weak AI are delegated to performing specific tasks. AI can further be classified into systems that can learn from data and use it to predict outcomes. This process is called machine learning. Machine learning can be supervised, unsupervised or reinforced. Training the system by supervising its learning through proper labeling of data results in its ability to predict outcomes. On the other hand, training the system with unlabeled data allows it to infer patterns and similarities among different data points. The system can also learn through trial-and-error by reinforcing the optimal solutions from a set of choices. A much wider usage of machine learning is called deep learning. Deep learning is done by giving vast amounts of data to the system and designing it in a way so that it can learn from numerical and non-numerical data, functioning almost like a human brain.

Advancements in machine learning and deep learning popularized generative artificial intelligence in the 2000s (Roman, 2023). It uses deep-learning models to generate any form of media such as text, images, graphics, sound, etc. based on training data (Martineau, 2023). Generative AI is deemed to be convenient for producing a desired type of content with a simple query or prompt by a user. A recently popular artificial intelligence program is a chatbot called ChatGPT. Created by OpenAI, it is a form of generative AI that uses the same concept of deep-learning material given by a large data set (University of Central Arkansas, n.d.). It is famous for providing quick yet detailed answers for any question given by a user, based on published references and other sources for data training. While ChatGPT leans more toward text generation, other generative AI programs or sites such as Midjourney, Adobe Firefly, DALL-E, Typecast, and Stable Diffusion generate images, sound, and other forms of media.

To such a degree, AI systems have been used in the field of medicine, finance industry, and facial recognition technologies (Uppal, 2023). In the field of medicine, AI is being used to revolutionize the industry by making the process faster than what humans can do. Some of the various applications of AI in the medical field are AI-led drug discovery, AI-assisted clinical trials, and patient care. AI also helps in reducing human errors especially for large volumes of data that hospitals and other medical related labs need. Additionally, AI-powered technologies such as healthcare robotics and AI-driven stethoscopes provide a way for more accurate diagnoses that is ultimately beneficial for patients. Despite these, AI in the medical field is still in its early stages and more research is still necessary (Shaheen, 2021).

Meanwhile in the finance industry, a paper published by Cao (2020) claims that AI have also been used in various applications such as market analysis, intelligent investment, blockchain technology, financial forecasting, and risk management. With the use of AI models designed for the finance industry, the risk factors can be lessened by making AI-driven analysis and forecasting. He then concluded that the advancements AI has been making is driving an new era of data and intelligence-driven economics and finance.

Despite these innovations, a conundrum emerges as society deems that AI possesses power that, if uncontrolled, can be devastating. Pazzanese (2020) notes that ethical concerns over the issues of privacy and bias that an AI system might step over are not baseless. Furthermore, the role of human judgment is also in consideration as suspicions of AI systems outright surpassing human intelligence arises. Generative AI, specifically, encountered intensive concerns as some of the popular generative AI programs rely on already available content and works from human creators, instead of the enormous data set used in deep learning and machine learning. This ignited controversy as evidence surfaced, showing that these programs collect training data from artists and creators without their consent or prior notice.

The artificial content produced by generative AI has circulated throughout social media platforms. In some cases, people fail to distinguish between manmade content and AI content. Furthermore, generative AI content can be deemed unnecessary as it fails to integrate with consumer behavior in an economic standpoint. A brand's adoption of generative AI induced negative behavioral follower reactions, affecting the brand's authenticity (Bruns & Meißner, 2024).

Other than ethical concerns, environmental concerns also plague AI systems due to its massive impact on nature. Ren and Wierman (2024) explain that accessing astronomical amounts of data consumes an alarming amount of electricity while also producing carbon emissions. This strain on electricity can lead to a rigorous burning of fossil fuels to match the needs of an AI system. Moreover, bodies of water are also affected as AI systems also require water for the cooling of servers or computers. Generative AI in general has a significant impact on energy consumption from training on large data sets. It is distinct from other labels of AI as it requires a tremendous number of calculations compared to traditional AI models. According to Vincent (2024), in the year 2022, data centers for AI and cryptocurrency used 460 terawatt hours of energy. They predict that in 4 years, it could increase to 620 or 1050 terawatt hours, which is equivalent to the energy consumption of Sweden or Germany respectively.

Objectives of the Study

The research aimed to identify the current awareness and understanding of students about the environmental implications of generative AI. It explored how frequently students use generative AI and their attitudes toward its sustainability. It explored the responses of college students from every course included in the study.

Statement of the Problem

The rapid rise in the popularity of advanced AI technologies has significantly impacted environmental welfare, including its scarcity of resources and severity of pollution. This study investigated the selected students' level of awareness regarding generative AI's environmental impact. The objectives were the following:

- Determining how often students use generative AI technologies for casual use and productivity.

- Assessing the students' awareness of generative AI's high demand for limited resources for its hardware platform, such as electricity, fresh water, and rare metals.

- Assessing the students' awareness of generative AI technology's direct effects on the environment such as:
    - High emissions of carbon footprint
    - Large contribution to the depletion of nonrenewable resources
    - Large contribution to producing electronic waste

- Comparing the answers of students in each course covered in the study.

Environmental Implications of Generative AI

Generative AI is rapidly expanding across various sectors, enabling machines to produce text, images, audio, and even video. These advancements, however, bring with them substantial environmental concerns primarily due to the immense computational requirements involved in training, deploying, and maintaining such models. As generative AI programs continue to grow, so too does their ecological footprint, making it essential to examine the environmental repercussions of these technologies in detail.

One of the most significant environmental concerns is energy consumption and carbon emissions. Large-scale generative AI models, such as Generative Pre-trained Transformers (GPT), require substantial computational resources throughout both the training and inference phases. This process generates considerable carbon emissions. For example, training a single large model like GPT-3 can result in carbon emissions equivalent to driving more than 240,000 miles in a passenger vehicle (Wu et al., 2022). As the size of model parameters increases, so does the need for energy, as more powerful infrastructure is required to support their development. In addition to direct electricity consumption, AI systems contribute to indirect emissions through the cooling systems used to maintain data centers. Although there have been efforts to improve energy efficiency, the rapid growth in computational demand continues to outpace these improvements, leading to a net increase in emissions (Bashir et al., 2024). It is estimated that global electricity consumption by data centers will reach between 620 and 1,050 TWh by 2026, posing significant challenges to sustainability goals, especially in terms of balancing carbon emissions and reducing greenhouse gas emissions.

Another critical aspect of generative AI's environmental effects is resource depletion and the effects of hardware production. Generative AI systems depend heavily on specific hardware like GPUs and AI accelerators, which significantly contribute to resource consumption. The extraction of rare earth minerals and metals for this hardware is energy-intensive and environmentally damaging, leading to habitat destruction, pollution, and the depletion of nonrenewable resources (Bashir et al., 2024). Furthermore, the production of hardware, particularly chips, requires significant amounts of water that leads to adding strain to water-scarce regions. The environmental effects extend throughout the hardware's lifecycle, from production to disposal, forming part of the embodied carbon footprint of generative AI systems. As AI systems scale, the demand for more powerful hardware worsens these environmental issues, making hardware production and maintenance unsustainable (Wu et al., 2022).

Despite efforts to improve efficiency, the rebound effect and other unintended consequences play a role in diminishing the potential environmental benefits of these advancements. The rebound effect occurs when improvements in energy efficiency lead to increased usage, ultimately driving up overall energy consumption (Bashir et al., 2024). For instance, as generative AI models become more efficient, they become more widely adopted across industries, which paradoxically increases their environmental burden despite improvements in per-task efficiency. Additionally, if the growth of AI technologies outpaces the development and adoption of renewable energy sources, industries may become further entrenched in the use of high-emission energy sources, delaying the transition to more sustainable practices.

Moreover, the ecological and system-level effects of generative AI are far-reaching. The expansion of data centers to meet the growing demand for computing power consumes vast areas of land and water, leading to habitat loss and reduced biodiversity in areas where these centers are located. The construction and operation of data centers can also cause environmental degradation, such as soil erosion and increased water usage. At a broader system level, the industrial shifts brought about by AI adoption can worsen environmental problems. For example, while AI innovations in energy management or design may improve efficiency, they can simultaneously increase overall consumption, undermining efforts to reduce the environmental footprint of these systems (Bashir et al., 2024).

Despite its environmental challenges, Generative AI also offers opportunities to support environmental research and communication. One notable benefit is its ability to streamline research workflows by enabling the creation of visual representations from text-based prompts, which can enhance communication between scientific communities and the public. For example, AI-generated images can represent conceptual models of climate change or illustrate complex ecological relationships, thereby aiding public understanding of environmental issues (Rillig et al., 2024). In addition, generative AI can assist in filling data gaps in environmental research, particularly in cases where regions are inaccessible or where instruments fail. AI models can predict missing data points, providing more complete datasets for analysis, particularly in fields such as remote sensing and biodiversity monitoring.

In addition to these environmental applications, the rise of models like ChatGPT and DALL-E has introduced broader implications for the use of generative AI. For instance, these systems that are based on large language models and neural networks can generate human-like text, images, and even music based on user input. For example, ChatGPT has made content creation, customer service, and education easier by automating tasks that traditionally required human effort. Similarly, DALL-E and many other image generation networks allow users to create unique, visually appealing images based on simple text prompts that change the face of art and design. While these advances boost productivity and creativity, they come with environmental concerns. The extensive computational power required by these models leads to energy consumption and carbon emissions, which raises sustainability questions regarding the environment. Moreover, the ease with which users, particularly students, can create content for academic assignments, social media, or other purposes can lead to greater and sometimes unnecessary computing demands, increasing carbon emissions as a result. Such a development not only spells doom to sustainable technology use but also has a broader implication on environmental issues such as increased energy consumption and depletion of natural resources. In addition, the social implications of generative AI, such as the loss of human employment, require responsible development and regulation to avoid technology advancement that significantly negatively impacts environmental and human well-being.

Students on Generative AI

Today's popularity of generative AI systems like ChatGPT is unmistakable. Due to this recent rise in popularity, extensive knowledge regarding generative AI is not yet common and accessible to the common folk. Thus, it is important to understand the perception and knowledge students have regarding generative AI, to establish whether they can also understand its environmental effects.

Wood and Moss (2024) investigated the usefulness of generative AI in teaching. In their study, students became comfortable enough with using generative AI that they can also understand its strengths and limitations as an instructional tool. The respondents believe that it has significantly helped them in their personal growth as well. Woods and Moss warn, however, that these positive results were achieved through a thorough guidance on how to use generative AI. This eliminates issues of bias, privacy, and misuse while allowing for an understanding on the implications of generative AI.

A study by Amoozadeh et al. (2024) focuses instead on the students themselves and their trust on generative AI. The researchers highlight that the students' trust in these new tools are critical because it gives them confidence to try it out and make use of it, allowing them to harness its potential. By interviewing computer science students who are more likely aware of how AI systems work, they were able to deduce that students have a mostly neutral view of generative AI but are wary of the outputs it provides, despite a majority having used generative AI for their own endeavors. The researchers also observed the difference regarding generative AI systems' inherent lack of transparency and the students' opinions that these systems are in fact transparent, which relates to the level of trust these students give to these systems.

Other studies also gave mixed results on generative AI, where students are both optimistic and reserved regarding generative AI. A select few are unaware, a generous amount do not use generative AI, but most agree that it is useful and there should be guidelines on where, how, and when to use it (Chan & Hu, 2023; Johnston et al., 2024). In particular, students see its usage in tasks such as grammar checking but frown upon its deeper usage in academics such as writing essays, believing it to be unfair and a form of plagiarism (Johnston et al., 2024). Chan and Hu (2023) reported that while their respondents mostly exhibit a positive attitude towards generative AI, they all still have their own concerns and issues regarding its implementation and potential usage in the future. Interestingly, Chan and Hu found that their respondents have a high expectation on the functionalities of generative AI but have a poor understanding of its limited emotional intelligence leading to insensitive outputs. They noted that AI literacy on students must be enhanced to allow them to use generative AI responsibly and request for a better approach regarding its integration into education.

ChatGPT itself was made to be the focus of the study of Abbas et al. (2024). According to them, the amount of workload and time pressure that a student is given increases their tendency to rely on generative AI. While those that are more sensitive to rewards, or fear being caught, are less likely to use generative AI. The study discovers that besides other concerns of generative AI, the overreliance of it causes students to have poor academic performance, procrastinate more, and even have memory loss. This is alarming especially if students are not made aware of these potential effects.

Several studies (Dai, 2024; Deschenes & McMahon, 2024; Obenza et al., 2023) affirm that students are using generative AI. Some reported that half of their respondents confirm using generative AI in their academic works. According to Deschenes and McMahon (2024), ChatGPT is the most used platform by students. Their respondents were reported to have a tendency to use generative AI in summarizing, getting feedback, and editing their works. Deschenes and McMahon noted that this could lead to an increase in generative AI usage in the future. Their respondents also expressed concerns on the negative impacts of generative AI on their learning. The respondents of Obenza et al. (2023) instead reported concerns over the negative impacts of generative AI in enhancing skills and the possibility of over-reliance on these systems. Despite these concerns, their respondents were still positive in using ChatGPT for academic works while maintaining a high level of awareness regarding the use of ChatGPT.

Research pertaining specifically to the environmental implications of generative AI are still not ample enough and so the perception of students on this topic is also lacking. However, it does not mean that students are not aware of the impact of technology on the environment. A study in the Philippines by de Mesa et al. (2022) recognizes that engineering students have high awareness regarding the impact of technology to the environment. E-waste and energy efficiency, for example, are some of the factors that received the highest awareness from the students in this research. Additionally, the students were reported to have a high level of commitment to environmental sustainability. The research affirms that Filipino students, specifically engineering students, do have some awareness of factors that affect the environment and willingness to take care of the environment. The results of Jahan and Mim's (2023) study reaffirms this statement through a different perspective. The students in their research were reported to be familiar with e-waste and its risks on the environment. Despite this, most of them were discovered to perform acts that are not sustainable to the environment such as not recycling e-wastes. This was not done out of intent but rather from a lack of information. The study found out that most students only have the internet as their source of information, leading to an insufficient knowledge on how to properly recycle e-wastes, programs regarding the recycling of e-wastes, and laws and regulations regarding e-wastes. The research demonstrates a possible outcome of the lack of knowledge regarding technology, and how students may want to perform acts that sustain the environment but cannot due to this insufficiency.

Because generative AI is becoming a trend in the present day, students are even more at risk of the potential demerits of generative AI and need a moderation to ensure its responsible usage. While students may use generative AI for their own purpose, they might not fully comprehend the repercussions of using it. The Philippines is a developing country, and so the need to determine the awareness and perception of students in the Philippines concerning generative AI becomes critical to avoid its misuse. Furthermore, the constant usage of generative AI for entertainment requires attention, especially because of the environmental impacts it can cause. The knowledge of students regarding generative AI's environmental implications needs to be checked in order to maintain its sustainable and responsible usage.

Method

Design

This research is a survey study under quantitative research. The research questions were addressed by gathering the perspectives of college students.

Locale

This study was conducted at Bulacan State University - Main Campus, located in Malolos, Bulacan. The respondents were the currently attending Bachelor of Science (BS) students in the College of Science at the time of this research. This college was selected as it offered courses such as BS in Computer Science that have the higher chance of having knowledge on how generative AI works due to the nature of their field. The college also houses several courses related to the environment such as BS in Environmental Science, BS in Environmental Science with Specialization in Climate Change and Disaster Management, and BS in Environmental Science with Specialization in Pollution Control Management, that aim to help the environment. These courses, along with other courses that have lower relation to generative AI, were expected to provide diverse perspectives of the topic, which is necessary in order to provide deeper insights on both Generative AI and its environmental implications. In doing so, the data can better represent the population at large, which aligns with the objective of this study.

Participants

The aim of this study is to establish the awareness of students. As such, a survey method was employed to gather sufficient data from the students. The letter submitted to the Dean of the College of Science Department requesting permission to conduct the survey was approved. This letter was then used to get the actual population of students in College of Science Department for the school year 2024-2025. The total population was 2173 across all 9 courses. The courses were the following:

- BS in Biology (BSB)
- BS in Environmental Science (BSES)
- BS in Environmental Science with Specialization in Climate Change and Disaster Management (BSES CCDM)
- BS in Environmental Science with Specialization in Pollution Control Management (BSES PCM)
- BS in Food Technology (BSFT)
- BS in Mathematics with Specialization in Applied Statistics (BSM AS)
- BS in Mathematics with Specialization in Business Application (BSM BA)
- BS in Mathematics with Specialization in Computer Science (BSM CS)
- BS in Medicinal Technology (BSMT)

A stratified random sampling was employed to ensure a statistically accurate data that includes at least one student from every course. A stratum was made to include all the sections of all year levels in every course needed in the study. Then, random sections were picked to be the representative of their respective course. The Cochran formula was used in determining the sample size of 327 with 95% confidence, 5% margin of error, and 0.5 proportion. The sample size was distributed proportionally based on the number of students attending each course. The demographic of the respondents according to their courses follows in Table 1.

Table 1. Frequencies of the respondents' courses

Course	Counts	% of Total	Cumulative %
BSB	69	21.1%	21.1%
BSES	20	6.1%	27.2%
BSES-CCDM	6	1.8%	29.0%
BSES-PCM	5	1.5%	30.5%
BSFT	48	14.7%	45.2%
BSM-AS	43	13.1%	58.3%
BSM-BA	46	14.1%	72.4%
BSM-CS	63	19.3%	91.7%
BSMT	27	8.3%	100.0%

Instrument

The initial instrument was developed by utilizing related studies and questionnaires that tackle on the perception of students on generative AI and the environmental implications of generative AI. The final version of the instrument contains two pages: the first page containing an infographic explaining how generative AI works and the second page containing a 5-point Likert scale with 9 items divided into 3 sections. The sections were comprised of the following:

1. How often do you use generative AI for the following purposes?
   - (p1.a) For casual use (entertainment, social media engagement, etc.)
   - (p1.b) For assistance in productivity (academic, professional, commercial, art, etc.)

2. Please indicate your level of awareness of the following implications related to generative AI. Generative AI highly demands the following resources:
   - (p2.a) Electricity
   - (p2.b) Rare metals used as materials for generative AI's data centers.(e.g. gold, copper, cobalt)
   - (p2.c) Fresh water used to cool generative AI's data centers

3. Please indicate your level of awareness of the following environmental implications related to generative AI.
   - (p3.a) Generative AI's platform produces a high amount of carbon footprint.
   - (p3.b) Generative AI's platform contributes to the depletion of nonrenewable resources.
   - (p3.c) Generative AI's platform produces a large amount of electronic waste.
   - (p3.d) Generative AI's platform has a large impact on the environment.

The sections employ a scoring that ranges from 1 (Never) to 5 (Always), from 1 (Fully Not Aware) to 5 (Fully Aware), and from 1 (Fully Not Aware) to 5 (Fully Aware), respectively. The 5-point Likert scale was determined following a similar instrument from the study of Paguigan and Jacinto (2018). All the questions in the survey were revised rigorously to align with the objectives of the study.

Validity

The instrument underwent content validation wherein three experts were asked to validate the survey. Using the guidelines from Yusoff (2019), the questionnaire received revisions from its performance on the content validity index based on relevance (CVI-R) and clarity (CVI-C).

Reliability

A pilot test was conducted where 30 students were selected using stratified random sampling and were asked to answer the questionnaire. A statistician was sought to perform a reliability test on the instrument using the data collected from the pilot test. Through the Jamovi software, the statistician determined the instrument's Cronbach alphas to be acceptable.

Procedure

The survey was distributed in person within designated areas of the Bulacan State University - Main Campus, and inside the respective classrooms of the chosen sections. The selected sections' mayors and their instructors present at the chosen time frame, when applicable, were approached and asked for their permission to survey the class. Respondents were given a maximum of 20 minutes to scan the infographic and finish the survey. Basic information of the respondents, such as course and year level, were also asked in the survey. Before handing out the survey, the respondents were given information about the objectives of the research, the assurance that their information will remain private, and the permission to call for the attention of the researchers should any concerns arise at any moment. They were also given candies and chocolates as a form of gratitude for giving their consent to participate in the research.

Data Analysis

The study reported all items with descriptive statistics. The first section's items, the frequency of students' use in generative AI tools, were assessed with measures of central tendency and frequency distribution tables, accompanied by histograms. The rest of the items were interpreted by measures of central tendency, along with diverging stacked bar graphs.

The Shapiro-Wilk test was used to determine the normality of each of the items' data. This test resulted with all the items having p-values of <.001. This led to all the items failing the normality hypothesis of the test, leading to use the non-parametric version of the one-way ANOVA, the Kruskal-Wallis test. In the Kruskal-Wallis test to identify significant relationships, only items with p-values less than 0.05 were selected and further elaborated. For each of the selected items, diverging stacked bar graphs were provided a descriptive comparison between the respondents' courses, as the independent variable; and data from the items' Likert scale, as the dependent variable. The use of this test was most appropriate as the data involved the relationship between multiple nominal groups and ordinal data.

The study used an open-source statistical platform, Jamovi, to compute for the collected data's measures of central tendency (median and mode), frequency distribution, the Shapiro-Wilk test, and the Kruskal-Wallis test. The researchers also used Microsoft Excel to illustrate the necessary figures such as histograms and diverging stacked bar graphs.

Results and Discussion

Descriptives

Table 2. Central tendency measures (median and mode) per item

Item	Median	Mode	Scale Median	Scale Mode
(p1.a) Casual	3	3	Sometimes	Sometimes
(p1.b) Productivity	4	4	Often	Often
(p2.a) Electricity	4	4	Aware	Aware
(p2.b) Rare metals	2	2	Not aware	Not aware
(p2.c) Fresh water	2	2	Not aware	Not aware
(p3.a) Carbon footprint	3	4	Neither aware nor not aware	Aware
(p3.b) Resource Depletion	3	2	Neither aware nor not aware	Not aware
(p3.c) E-waste	3	4	Neither aware nor not aware	Aware
(p3.d) Impact on environment	4	4	Aware	Aware

Frequency in Use of Generative AI Tools among Students

Casual use. From Table 2, both of item p1.a's median and mode indicate "Sometimes" as the most common response with 106 students (32.4%). From Table 3, the results indicate that 49.2% of the students never or rarely casually use generative AI tools, while 18.3% of the students often or always use those tools. This indicates that respondents moderately use generative AI for casual purposes, but with a tendency towards less frequent use.

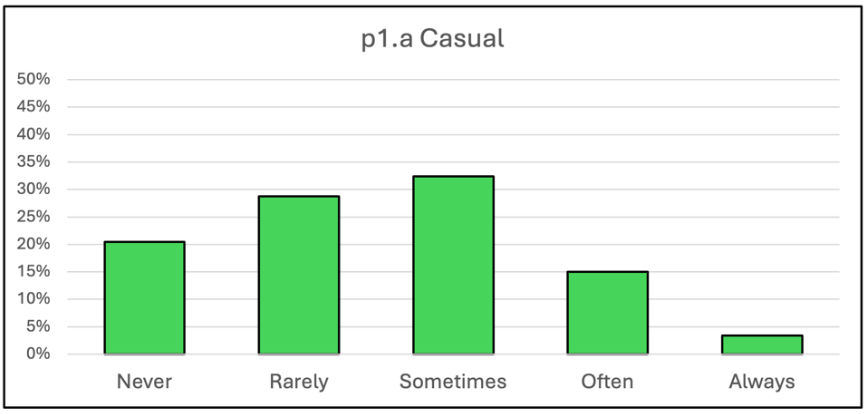

Figure 1. Histogram of the casual use of generative AI tools among respondents

Table 3. Frequencies of the casual use of generative AI tools among respondents

p1.a Casual			
Scale	Counts	% of Total	Cumulative %
Never (1)	67	20.5%	20.5%
Rarely (2)	94	28.7%	49.2%
Sometimes (3)	106	32.4%	81.7%
Often (4)	49	15.0%	96.6%
Always (5)	11	3.4%	100.0%

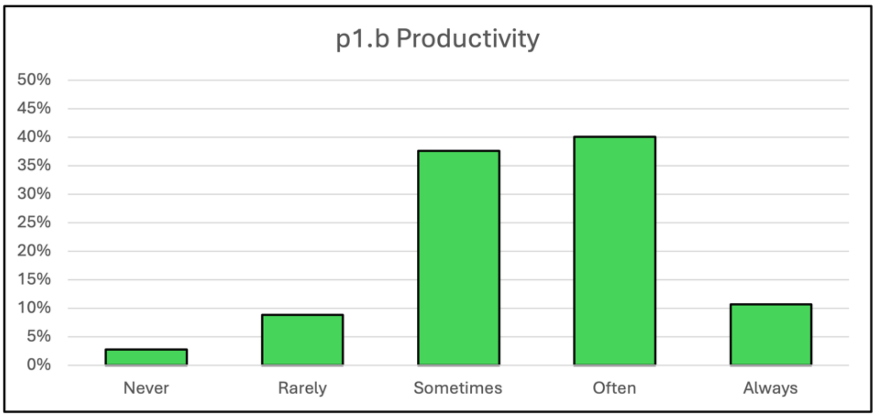

Figure 2. Histogram of the use of generative AI tools for assistance in productivity among respondents

Assistance in productivity. From Table 2, both of item p1.b's median and mode indicate "Often" as the most common response with 131 students (40.1%). From Table 4, the results suggest that 11.6% of the students never or rarely use generative AI tools for assistance in productivity, while 50.8% of the students often or always use those tools. This indicates how the students often use generative AI as assistance in their productivity purposes.

Table 4. Frequencies of the use of generative AI tools for assistance in productivity among respondents

p1.b Productivity			
Scale	Counts	% of Total	Cumulative %
Never (1)	9	2.8%	2.8%
Rarely (2)	29	8.9%	11.6%
Sometimes (3)	123	37.6%	49.2%
Often (4)	131	40.1%	89.3%
Always (5)	35	10.7%	100.0%

Students' Awareness on Generative AI's Resource Demands

From Figure 3, 41% of the respondents answered with "Aware" on generative AI's demand for electricity, which marks both the median and mode from Table 2. Conversely, awareness on generative AI's demand for rare metals and fresh water both receive a median and mode of 2 (Not Aware), the response being 40% and 42%, respectively. This indicates that the respondents are generally aware of generative AI's electricity demand, but they are mostly unaware of generative AI's demand for rare metals and fresh water.

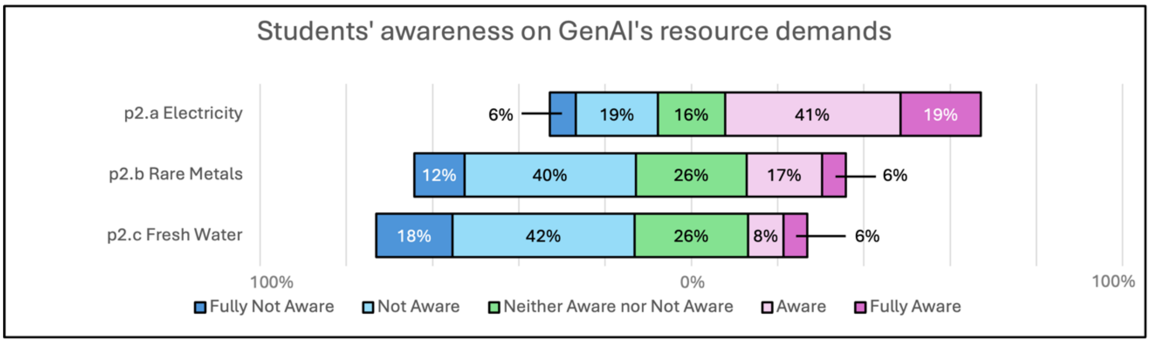

Figure 3. Diverging stacked bar graph of students' awareness on generative AI's resource demands

Students' Awareness on Generative AI's Environmental Implications

From Figure 4, the respondents were generally aware of generative AI causing a significant impact on the environment, with 37% and 20% of them answering "Aware" and "Fully Aware," respectively, marking 4 (Aware) as both the data's median and mode. However, the data provides an unclear consensus among respondents with generative AI's sub-implications on the environment, as the awareness levels are mostly split. Each of the first three implications' data show a mismatch between median and mode.

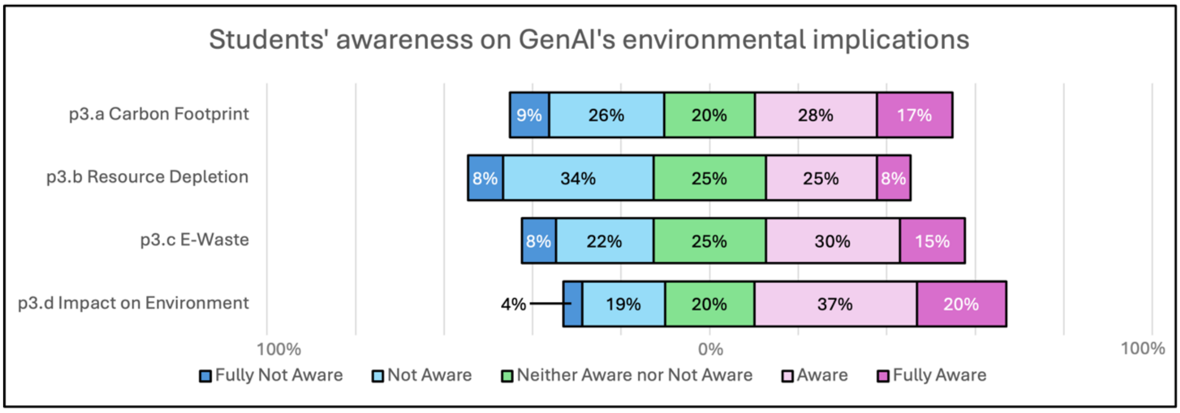

Figure 4. Diverging stacked bar graph of students' awareness on generative AI's impact on the environment

From Table 2, the data on the implications of generative AI's carbon footprint (p3.a) and e-waste (p3.b) both have a median of 3 (Neither Aware nor Not Aware) and a mode of 4 (Aware). This may suggest a distribution close to being balanced, but it still skews towards the most common response (Aware). Also from Table 2, data from the implication of its resource depletion (p3.b) also has a median of 3 (Neither Aware nor Not Aware), but it has a mode of 2 (Not Aware). This may also suggest a distribution close to being balanced, but it still skews towards the most common response (Not Aware).

Comparisons among Courses

From Table 5, with each item having degrees of freedom (df) of 8, items p1.b, p3.a, and p3.c have p-values less than 0.05, showing statistical differences among the responses of the stratified groups, within the highlighted items. Item p1.b possesses a small effect size (ε^2) with 0.0507, while items p3.a and p3.c each possess a medium effect size (ε^2) with 0.1353 and 0.1068, respectively.

Table 5. Kruskal-Wallis p-values for group (course) comparisons

Item	X^2	df	p	ε^2
(p1.a) Casual	10.63	8	0.224	0.0326
(p1.b) Productivity	*16.53*	*8*	*0.035*	*0.0507*
(p2.a) Electricity	11.53	8	0.174	0.0354
(p2.b) Rare metals	9.54	8	0.299	0.0293
(p2.c) Fresh water	11.56	8	0.172	0.0355
(p3.a) Carbon footprint	*44.12*	*8*	*<.001*	*0.1353*
(p3.b) Resource Depletion	13.21	8	0.105	0.0405
(p3.c) E-waste	*34.81*	*8*	*<.001*	*0.1068*
(p3.d) Impact on environment	11.72	8	0.164	0.036

From Figure 5, the data indicates that BSMT students use generative AI the most for productivity purposes, with 81% of their responses being "Often" or "Always," followed by BSES and BSM-CS with 65% and 55%, respectively. However, the effect of attending a specific program on the usage of generative AI for productivity is relatively modest, due to its small effect size (ε^2) in Table 5.

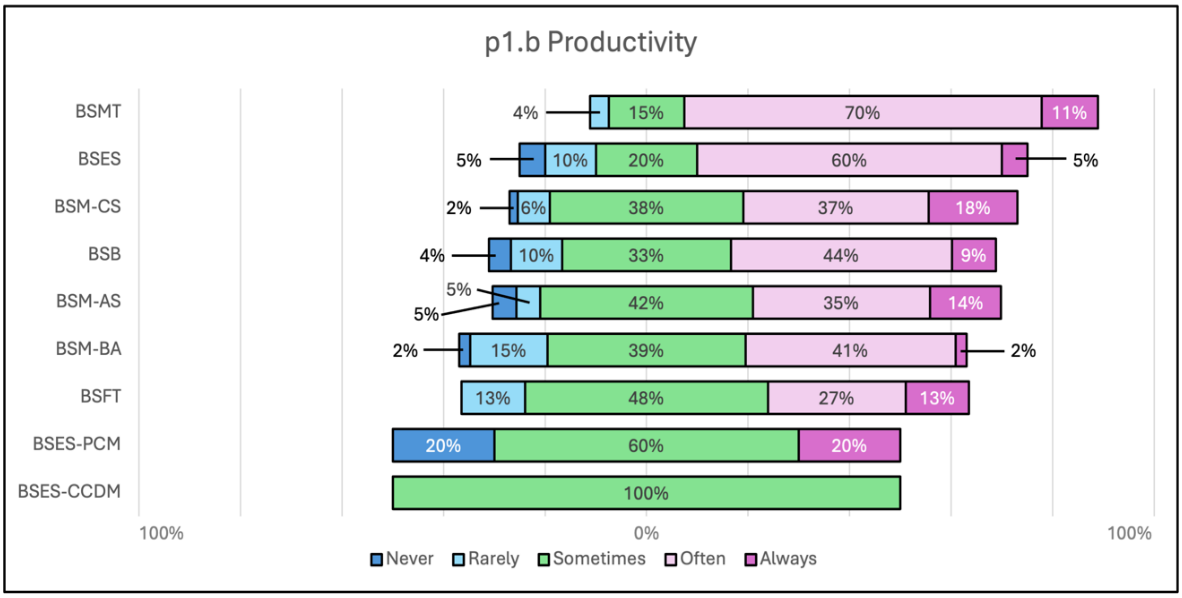

Figure 5. Diverging stacked bar graph of students' usage of generative AI for productivity among each course

From Figure 6, the data indicates that BSES students are the most aware of generative AI's carbon footprint, with 95% of their responses being "Aware" or "Fully Aware," followed by BSES-PCM and BSMT with 80% and 71%, respectively. From Figure 7, the data indicates that BSES-PCM students are the most aware of generative AI's e-waste production, with 80% of their responses being "Aware" or "Fully Aware," followed by BSES and BSMT with 75% and 74%, respectively.

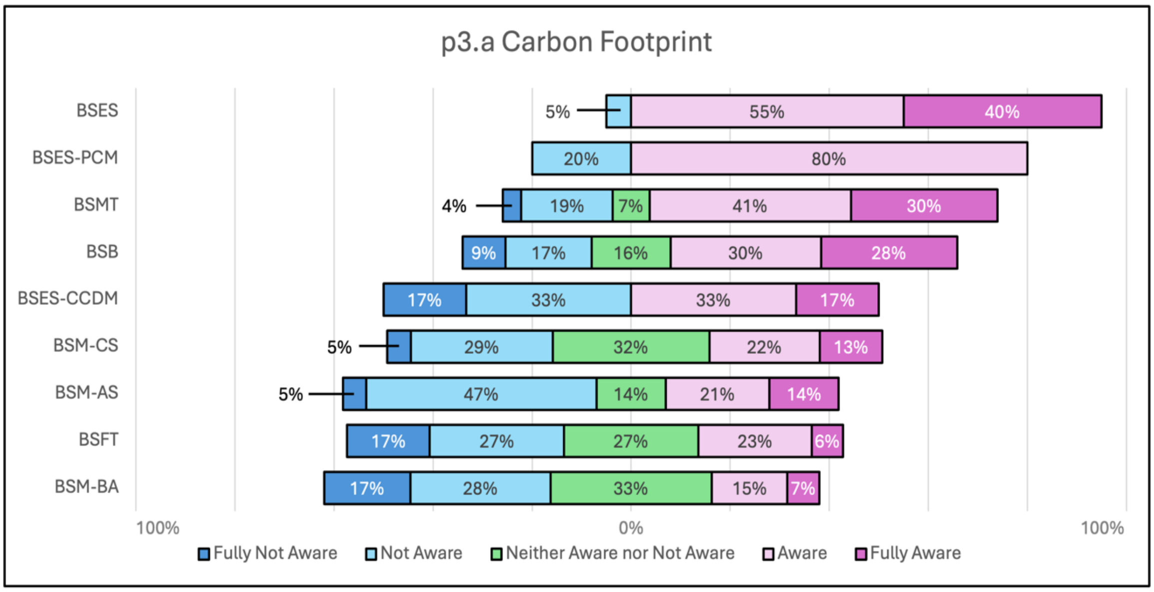

Figure 6. Diverging stacked bar graph of students' awareness on generative AI's carbon footprint among each course

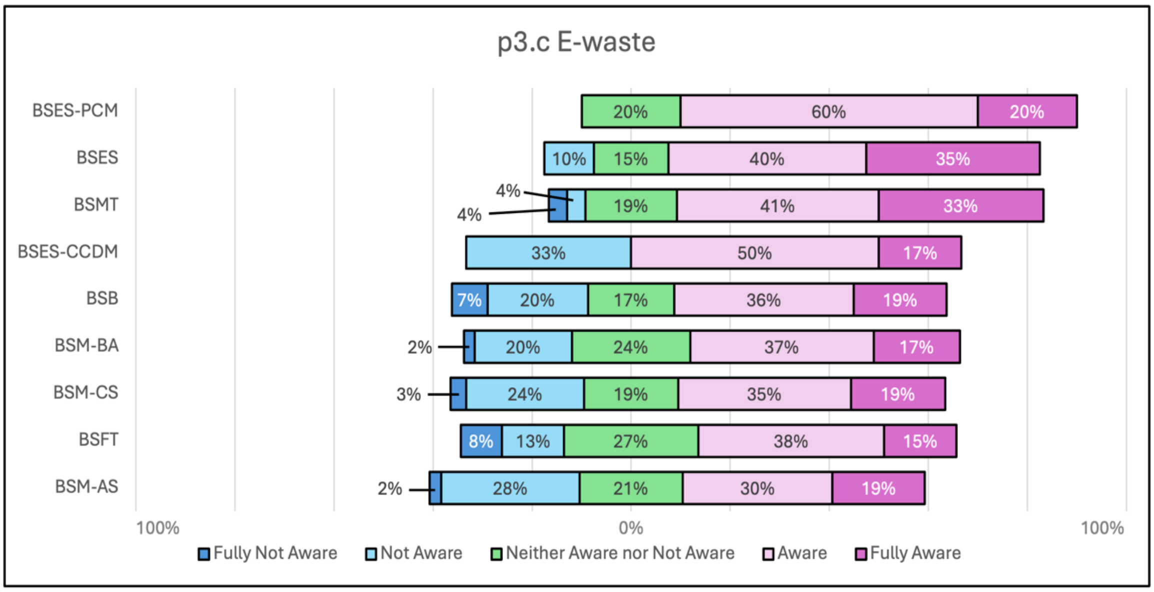

Figure 7. Diverging stacked bar graph of students' awareness on generative AI's contribution to e-waste among each course

Findings

The first objective of this study was to determine how the students use generative AI tools. The study coincides with other studies on this topic that students do use generative AI, and the data reflects that the usefulness of these tools is seen as a boon for productivity. However, the data also reveals that students do not actually have a high tendency to use generative AI. It only appears to be used sparingly, especially for productivity.

The next objective was to assess their awareness on the resource demands of generative AI. Having consistent values of the median and mode, the data shows that the respondents are only aware of the electricity demands of generative AI. This is alarming as poor understanding of these demands can shrink the severity of its misuse. The students' awareness on the electricity demands of generative AI could be due to its relation to devices. Students may be more inclined to think that generative AI generally has a high electricity demand since it is accessible through their own devices, such as computers, which have a high electricity demand in the first place. Additionally, media coverage about generative AI rarely fully explains the data centers it utilizes which is the main cause of the resource demands. The curriculum of students rarely touches upon and explains fully the topic of generative AI which might also explain their poor understanding. Another thing to note is that the data points to the respondents being aware and not fully aware of its electricity demands. Perhaps their awareness needs to be elevated in all these categories.

Assessing the awareness of the students on environmental effects of generative AI proved to be difficult. The data displayed mixed results regarding each item in this section, as evidenced by the varying values of the median and mode on each item. The only universal answer was that generative AI does influence the environment. The data shows that while some students are aware of generative AI's carbon footprint and e-waste production, a significant portion of them do not have a clear understanding of these specific effects altogether. At the same time, the students are also not confident with their stance on the awareness of generative AI's resource demands, but most of them are clearly not aware of this effect. The diverse opinions may signify that the respondents have certain awareness regarding its environmental implications, but their knowledge on it does not have sufficient depth to specifically identify these effects.

Implication of the Results on the Respondents' Courses

Comparisons can be made regarding some of the data that was determined to have high statistical differences. Investigating the reason why BSMT and BSES students have a notable usage on generative AI tools may be of value to future researchers. In accordance with this information, BSES and BSMT students also showed some of the highest amounts of awareness per student on generative AI's carbon footprint and contribution to E-waste. Further studies should cover how the awareness of these courses can be applied in promoting the awareness of other courses.

The differing curriculum of each course is a factor to consider when observing the results obtained. BSES students are expected to have knowledge regarding this topic due to their curriculum, but they still retained a notable usage of generative AI tools. Their knowledge and confidence in avoiding or lessening the impacts of generative AI on the environment may also be a cause in their significant usage of it. On the other hand, the awareness and usage of BSMT students on generative AI might be attributed to the great value generative AI provides in the medical field (Reddy, 2024). Given the wide range of benefits, BSMT students might also be knowledgeable in these aspects and therefore incorporate generative AI in their practices. In addition, the workload given to BSMT students, who are often instructed to read and memorize information in their field, might increase their tendency to rely on generative AI in helping them in their studies. External factors such as the environment and professors the students have can also explain why they showed such results in the study. Due to the varying factors at play, further exploration on this occurrence is needed.

It can also be observed that BSES-PCM and BSES-CCDM students, BSES students with specializations, are evidently not displaying similar opinions. BSES-PCM students were reported to be one of the highest courses regarding the awareness on generative AI's carbon footprint and contribution to e-waste, but BSES-CCDM students were either equally aware and not aware or only leaning towards aware. This may suggest a difference in their curricula or a difference in the overall opinion of the students under these courses.

Limitations of the Research

The study only surveyed college students under the College of Science Department in Bulacan State University - Main Campus. This was selected because they had the highest potential to have sufficient knowledge on generative AI to answer the questionnaire. Students in other college departments who may not have sufficient knowledge regarding generative AI and its environmental implications yet use these tools unknowingly or regularly are worthy of investigation. The BSES-PCM and BSES-CCDM students were only made up of first-years due to its recency, leading to a small sample size on these courses. Further research regarding this topic should be made when these courses have higher total populations. Lastly, the quantitative nature of this study limits the investigation on this topic. Other methods should be used to explore this topic even further.

Recommendations

Based on the findings of this study, an infographic is proposed that aims to further enhance the awareness of students regarding the environmental implications of generative AI (Figure 8).

Figure 8. The proposed infographic the researchers designed

The researchers suggest an infographic because of its ease in spreading information and its ability to capture attention with its colorful details. The infographic contains concise but adequate information regarding this topic to remain easy to understand and not hard to read. The infographic is made with the goal of steadily elevating the awareness of students. The proposal acts as the first step in educating students on the environmental implications of generative AI and it also serves as a warning on the dangers of its misuse.

Besides the proposed infographic, other ways to disseminate information such as hosting programs, educational workshops, and social media posts are also recommended. For school administrators, specifically, including the implications of generative AI as a topic to discuss in the curriculum of relevant courses as well as encouraging instructors to warn students regarding said effects can greatly benefit in spreading further awareness on the possible misuse of generative AI.

Future researchers may examine the efficiency of the infographic in increasing awareness. Furthermore, investigating the source of knowledge and awareness of students regarding the environmental implications of generative AI and generative AI itself, can prove to be beneficial in developing other methods of increasing awareness. Future researchers may replicate this study and compare their findings, determining whether this study supports or contradicts their results. Lastly, additional studies relating to this topic are essential as the current depth of knowledge is not as extensive as other fields yet.

Conclusion

Generative AI is a powerful tool that has already reshaped the lives of many. If used correctly, it can help people's lives and work. The problem arises with its misuse and the dangers it may cause in society and the environment. This newfound popularity on tools like ChatGPT increases this likelihood, specifically on students. Its demand on electricity, rare metals, and freshwater can further worsen with each misuse of the servers that generate AI content. Furthermore, these servers also produce a large amount of carbon footprint, consume nonrenewable resources, and add to the growing amount of e-waste in the environment. The knowledge of students regarding these environmental implications is crucial in ensuring that the consequences of its misuse are addressed and acknowledged, serving as a warning to the students themselves.

The research establishes that the students have some awareness of the environmental implications of generative AI. The students were also able to assess their usage of these tools which was further magnified by the infographic given to them, allowing them to further identify the tools they use. Despite using it mostly for productive reasons, the students show a shallow understanding on the numerous environmental implications of generative AI. The study reported weakness in the understanding of the rare metals and freshwater that the servers use as well as the nonrenewable resources it diminishes. BSMT and BSES students were found to have the highest tendency to use generative AI. Both courses also displayed considerable awareness on the environmental implications of generative AI. On the other hand, BSES-PCM students displayed consistent awareness on these implications while not particularly using these tools regularly.

Further research on these topics should investigate the deeper correlation of the students' usage of generative AI and their awareness on its environmental implications. Investigating where these students learn and expand their knowledge on the environmental implications of generative AI may contribute greatly to increasing the awareness of students at large. In addition, exploring the extent of the students' usage of generative AI can help gain insights on whether the tools are being used appropriately and ethically.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflicts of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Funding Declaration

The authors did not receive support from any organization for the submitted work.

Acknowledgements

We owe the results of this paper to those who extended their hands to us. We extend our gratitude to our instructor, Eleonor Basilio Ph.D., who gave insightful remarks and critiques for the betterment of our paper. We would equally like to thank our College of Science Department of the Bulacan State University - Main Campus and our dean, Thelma Pagtalunan Ph.D., for giving us the resources and allowing us to conduct this study. The guidance provided to us by the chairperson of our department, Asst. Prof. Harris Dela Cruz, will also not be remiss by us. Our sincere appreciation goes as well to our statistician, Aarhus Dela Cruz LPT MSc, and to our validators, Christian Gacila, John Conrad Nunag, and Mark Andrew Castel, who helped us immensely in our study. Lastly, we offer our heartfelt gratitude to our families, friends, and classmates, especially, Fiona Ventura and Mark Oliver Medina, who provided the needed assistance in the completion of our study. Their unwavering support has been a great motivation in our undertaking.

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Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025 https://doi.org/10.55549/jeseh.800

Artificial Intelligence in Early Childhood STEM Education: A Review of Pedagogical Paradigms, Ethical Issues, and Socio-Political Implications

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Article Info

Article History

Published:
01 April 2025

Received:
28 January 2025

Accepted:
22 March 2025

Keywords

Artificial Intelligence
Early Childhood STEM Education
Pedagogical Paradigms
Ethical Issues
Educational Policies

Abstract

This study examines the pedagogical, ethical, and political dimensions of artificial intelligence (AI) in early childhood STEM education from a theoretical perspective. As digital technologies become increasingly prevalent in education, AI applications offer significant opportunities in areas such as personalized learning experiences, game-based education, and data analytics. However, they also pose critical ethical concerns, including data security, algorithmic bias, and privacy, while influencing children's cognitive, linguistic, and social development. Drawing on Piaget's theory of active discovery and learning, Vygotsky's emphasis on social interaction and teacher guidance, and Bronfenbrenner's ecological systems theory, this study explores how AI-supported learning environments can enrich children's natural developmental processes. A qualitative literature review and theoretical analysis reveal the necessity of achieving a balanced integration between the individualized educational opportunities offered by AI and the potential risks it entails. The findings highlight the critical importance of developing human-centered, ethically sound, and inclusive educational models for educators, policymakers, and researchers in the face of technological transformation. In this context, teacher training, parental collaboration, and interdisciplinary strategies are identified as fundamental prerequisites for the sustainable and effective integration of AI in early childhood education.

Introduction

The rapid advancement of digital technologies is reshaping education systems and introducing new paradigms in learning processes (Selwyn, 2019). Artificial intelligence (AI) presents significant opportunities in areas such as personalized learning, student performance analytics, and the adaptability of educational materials (Luckin, 2017). While research on AI in education has largely focused on higher education and K-12 levels, its pedagogical implications in the context of early childhood education remain insufficiently explored (Ng, 2021). However, early childhood is a critical period for cognitive, social, and emotional development, and pedagogical approaches implemented during this stage have long-term effects on learning processes (Shonkoff & Phillips, 2000). Therefore, examining how AI can be utilized in early childhood education, under what conditions, and what ethical and policy-related questions it raises is of particular significance for both academic and applied research.

Recent studies indicate that AI-assisted tools are being integrated into early childhood education in various ways. For instance, robot-assisted teaching environments (Tanaka & Matsuzoe, 2012), adaptive learning systems (Zhu & Xie, 2021), and natural language processing-based storytelling applications (Chambers et al., 2019) have been shown to positively influence children's cognitive and linguistic development. However, ongoing debates persist regarding AI's long-term effects on children and its appropriate positioning within pedagogical processes (Holmes et al., 2021). Key areas requiring further research include how AI affects teacher-child interactions, shapes learning processes, and transforms children's play-based learning experiences (Zhao et al., 2022).

From a pedagogical paradigm perspective, a fundamental research question concerns the extent to which AI-supported educational applications reinforce or transform traditional teaching approaches. In constructivist learning theories (Piaget, 1952; Vygotsky, 1978), active participation and exploration play a central role in children's learning processes. However, how AI facilitates or constrains these processes remains inadequately understood (Blikstein, 2018). Additionally, AI applications based on behaviorist teaching models have been criticized for potentially promoting rote and mechanical learning rather than fostering deeper cognitive engagement (Papert, 1980; Resnick, 2017). Thus, determining which educational philosophies align with AI and how AI can be effectively integrated into pedagogical processes is a key focus of this study.

AI-supported learning environments also raise significant ethical and policy-related concerns. Issues such as child privacy, data security, and algorithmic bias are among the primary ethical concerns regarding AI in education (Borenstein & Howard, 2021). For example, AI-based learning systems that analyze children's behaviors and collect large-scale data pose substantial risks in terms of child rights and data security (Livingstone & Stoilova, 2020). Furthermore, the widespread implementation of AI in early childhood education may exacerbate educational inequalities (Eynon & Williamson, 2020). Schools with limited access to resources may struggle to benefit from AI technologies, deepening the digital divide in education (Falcer & Selwyn, 2013). Therefore, shaping educational policies to address both the pedagogical and ethical dimensions of AI is another critical aspect of this study.

In this context, this study aims to examine the use of AI in early childhood education through the lens of pedagogical paradigms, ethical issues, and policy implications within a theoretical framework. By systematically analyzing contemporary perspectives in the literature, this research seeks to determine how AI can be effectively utilized in early childhood education and within which ethical and policy frameworks its application should be evaluated. Ultimately, this study aims to contribute to the academic discourse and educational policy development by highlighting the pedagogical potential, limitations, and future directions of AI in early childhood education.

Method

Research Design

This study adopts a qualitative literature review and theoretical analysis approach to comprehensively examine the pedagogical, ethical, and policy dimensions of artificial intelligence (AI) in early childhood education. The primary aim of the research is to explore the impacts of AI on early childhood education and to analyze its implications for pedagogical approaches, data security, ethical concerns, and educational policies. Through a systematic review and critical synthesis of contemporary perspectives in the literature, this study seeks to integrate theoretical contributions from various disciplines (Okoli & Schabram, 2010; Webster & Watson, 2002). The central assumption of the research is that AI applications exert a broad influence on early childhood education, affecting multiple dimensions ranging from pedagogical practices to data security and ethical values. Accordingly, this study adopts a comprehensive and interdisciplinary perspective (Merriam, 2009; Yin, 2014).

This process aims to identify gaps in the literature and highlight innovative approaches. To achieve this, the literature review was conducted in accordance with the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Page et al., 2021). Initially, a systematic search was performed in international academic databases, including Web of Science, Scopus, ERIC, ProQuest, TRDizin, EBSCO, and Google Scholar, using key terms such as "early childhood education," "artificial intelligence," "pedagogical paradigms," "ethical issues," and "educational policies". Boolean operators and filtering techniques (Okoli & Schabram, 2010; Webster & Watson, 2002) were applied to prioritize peer-reviewed articles, reports, and conference proceedings published after 2010.

Data Collection

The data collection process was based on a systematic review of relevant peer-reviewed articles, books, reports, and conference proceedings. The study primarily relied on international academic databases such as Web of Science, Scopus, ERIC, ProQuest, TRDizin, EBSCO, and Google Scholar. Additionally, reports and policy documents published by international organizations such as the OECD, UNESCO, and the European Commission were also included in the analysis. The selection criteria prioritized peer-reviewed journal articles published after 2010, recent books, and international reports. A comprehensive search strategy was applied using Boolean operators and filtering techniques with key terms such as "early childhood education," "artificial intelligence," "pedagogical paradigms," "ethical issues," and "educational policies".

The initial search identified 283 studies related with artificial intelligence among early childhood period, which were then assessed based on their titles, scope, and abstracts. Following this evaluation, 112 studies were selected for detailed content analysis. Subsequently, 75 studies that did not directly contribute to the study’s objectives or provided only limited discussions within the broader context of educational technology were excluded. Ultimately, 37 studies were subjected to in-depth content analysis. In other words, studies focusing on AI, early childhood education, pedagogical paradigms, ethical concerns, and educational policies were included, while those with only a general focus on educational technology were excluded. As a result, 37 studies were found to be directly relevant to the objectives of this research.

Data Analysis

The content analysis process employed thematic coding, identifying three main categories: pedagogical approaches, ethical concerns, and educational policies. In this process, reliability measures for content analysis proposed by Miles and Huberman (1994) were followed, achieving an inter-coder agreement of 85%. This ensured a transparent and replicable structure for the systematic review and thematic analysis (Merriam, 2009;Yin, 2014).

Initially, the collected data were categorized thematically using qualitative analysis techniques. Subsequently, the relationships between pedagogical theories, AI technologies, and ethical principles were systematically synthesized. This synthesis facilitated the development of a multidimensional theoretical model explaining AI integration in early childhood education. Furthermore, comparative analyses were conducted between traditional educational models and AI-assisted approaches, evaluating their respective strengths and weaknesses from a theoretical perspective. These comparisons reinforced the arguments regarding the applicability of the proposed model (Chen et al., 2020; Luckin et al., 2016).

The collected data underwent a two-stage analysis process. In the first stage, prominent pedagogical approaches, ethical issues, and policy recommendations in the literature were examined using content analysis. Each study was systematically coded according to specific themes, following the methodological principles outlined by Miles and Huberman (1994). In the second stage, the identified thematic findings were synthesized through a critical review. This synthesis process focused on evaluating similarities, differences, and contradictions across studies, thereby enabling a comprehensive interpretation of the multidimensional impacts of AI in early childhood education (Cooper,1988; Webster & Watson, 2002).

Validity and Reliability

In qualitative research, validity and reliability play a crucial role in interpreting findings (Yin, 2014). Therefore, this study employed strategies such as a systematic approach and critical review. Comparative analysis of diverse data sources ensured consistency in findings, while the rigorous application of inclusion and exclusion criteria enhanced the replicability and reliability of the study's results (Okoli & Schabram, 2010). Furthermore, critically evaluating sources allowed for a careful consideration of methodological limitations and potential biases (Merriam, 2009). Nonetheless, the methodological approach acknowledges that qualitative analyses based on literature reviews are inherently subject to subjective interpretations. The limitations of the inclusion criteria and search strategies used in source selection may introduce potential biases that could influence the study’s overall conclusions. However, efforts were made to minimize these limitations by utilizing a broad and interdisciplinary data pool (Yin, 2014).

Model Development Process and Methodological Foundations

The primary aim of this study is to develop a theoretical model addressing the integration of artificial intelligence (AI) into early childhood education from pedagogical, ethical, and policy perspectives. The development of this model is based on a systematic literature review and thematic content analysis. The process of constructing the model involved the following key stages:

The first stage focused on literature review and theoretical framework identification. The model was built upon an extensive review of existing theoretical approaches in early childhood education and AI. The foundational theories incorporated into the model include Piaget’s theory of discovery-based learning, Vygotsky’s social interaction and guided learning approach, and Bronfenbrenner’s ecological systems theory.

The second stage involved systematic literature analysis and thematic coding. The literature review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Initially, 283 studies were identified, out of which 75 studies that did not meet the inclusion criteria were excluded. Consequently, a total of 37 key studies were selected for in-depth content analysis.

In the third stage, data analysis and thematic model construction were carried out. The thematic analysis identified three core dimensions: pedagogical approaches, ethical concerns, and educational policies. Coding methods by Miles and Huberman (1994) were employed, ensuring an inter-coder reliability rate of 85%, thus enhancing the consistency of the content analysis.

The fourth stage focused on structuring the model and defining the conceptual framework. The final model highlights the integration of AI in early childhood education across three critical dimensions:

- Pedagogical Paradigms (Discovery-based learning, AI-supported social interaction, game-based learning)
- Ethical Issues (Data privacy, algorithmic bias, equity in education)
- Policy and Strategic Approaches (AI-driven education policies, teacher training, regulatory frameworks)

To enhance the validity and reliability of the model, comparative analyses with existing AI-based educational models were conducted. The proposed model was compared with AI education frameworks developed by Chen et al. (2020) and Luckin et al. (2016), highlighting both similarities and differences. This methodological approach ensures that the model is both theoretically grounded and practically applicable, reinforcing its contribution to the academic literature. Future research should focus on empirical validation of the model through experimental and applied studies in early childhood education settings.

Findings

The findings of this study were constructed using systematic literature review and critical synthesis methods. The role of artificial intelligence (AI) in early childhood education, its integration into pedagogical practices, concerns related to data privacy and ethics, and the frameworks of national and international policies were examined across different dimensions in the literature. The data obtained indicate that AI provides both positive contributions and certain risks to pedagogical paradigms. Furthermore, the study revealed that at the ethical and political levels, there are ongoing multi-layered debates, with significant gaps, especially regarding data security, algorithmic bias, and digital inequality.

Thematic Model: AI-Supported Early Childhood STEM Education

Some models developed within the political framework aim to strengthen collaboration among government institutions, educators, technology providers, and parents. These strategies are structured around the principles of transparency, participation, and accountability, with the goal of aligning AI applications with pedagogical and ethical dimensions. To clarify this aspect of the study,

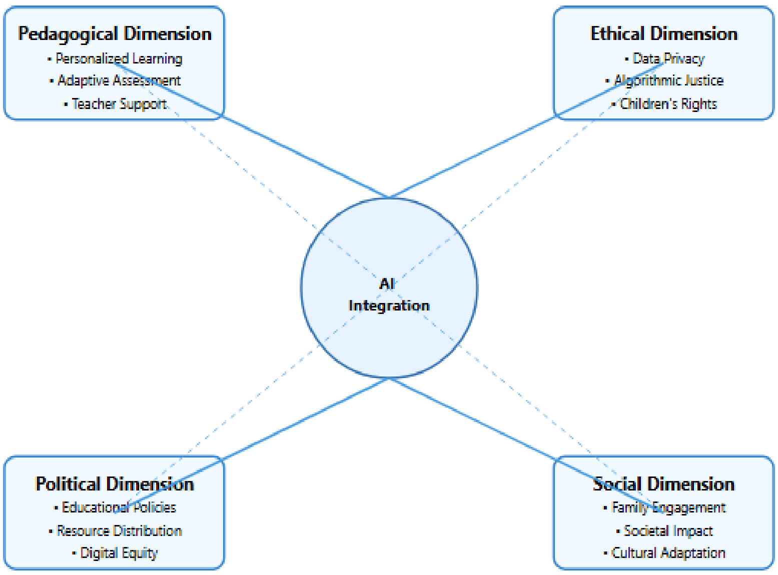

Figure 1. Conceptual framework: integration of artificial intelligence in early childhood education - a multi-dimensional interaction model

Figure 1 presents a conceptual model showing the interaction between policy, pedagogical practices, and ethical principles in AI integration in early childhood education, based on the data collected in this study. This model visualizes the challenges faced by policymakers and practitioners, along with proposed solutions, while also indicating areas for strategic intervention. In Figure 1, the conceptual model illustrates how AI integration interacts with pedagogical practices in early childhood education, while also considering the ethical concerns, policies, strategic orientations, and teacher-parent relationships. This model visualizes the interrelations and feedback loops among all dimensions, summarizing the multilayered effects of technology on the educational field.

To systematically analyze the integration of artificial intelligence (AI) in early childhood education, a thematic model was developed (Figure 2). This model conceptualizes AI integration across three critical dimensions: pedagogical paradigms, ethical and data security issues, and educational policies and strategies. The pedagogical paradigms dimension draws upon established educational theories, including Piaget's discovery-based learning approach, Vygotsky's emphasis on social interaction, and Bronfenbrenner's ecological systems theory. These theoretical perspectives provide insight into how AI-enhanced learning environments can either support or challenge traditional early childhood education (ECE) practices.

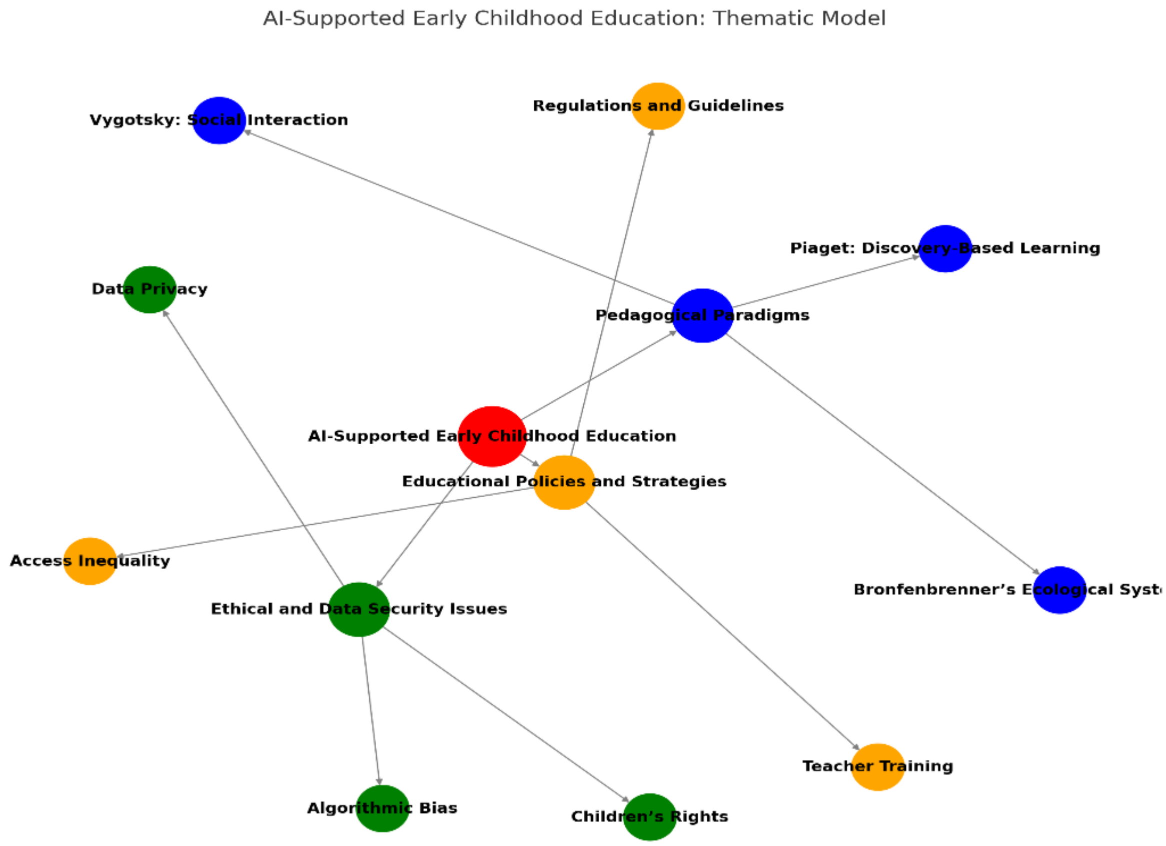

Figure 2. Thematic model of AI-supported early childhood education

The ethical and data security issues dimension highlights key concerns related to AI implementation in ECE, including algorithmic bias, data privacy, and children's rights. As AI-based educational tools increasingly collect and process large amounts of data, ensuring transparency, security, and fairness in their design and application becomes imperative.

The educational policies and strategies dimension underscores the need for structural frameworks to regulate AI adoption in early childhood settings. It includes essential policy considerations such as teacher training, access inequality, and regulatory guidelines. Given the potential disparities in AI accessibility across different educational contexts, strategic policymaking is required to bridge digital divides and foster equitable AI integration.This thematic model offers a multidimensional perspective on AI's role in ECE, demonstrating the interconnectedness of pedagogical, ethical, and policy-related factors. The conceptual framework serves as a foundation for discussing the opportunities and challenges of AI implementation in ECE and provides insight into future directions for research and practice. The overall assessment of the findings reveals that AI applications in early childhood education have multidimensional effects. These effects can be optimized through the integration of pedagogical efficiency, ethical responsibilities, and strategic policymaking processes. The data suggests that, with careful planning and regulatory frameworks in place, AI's potential can lead to innovative educational practices; otherwise, the technological adaptation process might produce unintended side effects.

In this study, based on international databases and recent reports, three main dimensions of AI applications in early childhood education—pedagogical paradigms, ethical issues, and political orientations—were systematically examined. The critical synthesis of the studies in the literature resulted in the following key findings, presented below with their subdimensions.

Pedagogical Paradigms

The reviewed studies indicate that AI applications play a significant role in enriching learning processes in early childhood. Research highlights that AI-supported tools foster individualized learning experiences, contributing to children's cognitive, linguistic, social, and emotional development. For instance, Aslan et al. (2024) and Kewalramani et al. (2021) focus on interactive and play-based models to support learning processes, while Jin (2019) and Liu and Kromer (2019) emphasize the pedagogical value of exploration and problem-solving approaches in early childhood. Furthermore, Masturoh et al. (2024) and Solichah and Shofiah (2024) demonstrate that increasing children's digital literacy and collaborative learning skills through digital games and activities positively contributes to learning processes.

Findings on the pedagogical impact of AI in early childhood education suggest that, in most related studies, technology-supported learning environments create individualized educational opportunities. Experimental research by Shin et al. (2020) reports significant increases in problem-solving skills and cognitive flexibility in children when they are exposed to AI-supported interactive, game-based learning environments. Similarly, studies by Mubin et al. (2013) show that robotic applications strengthen social interaction and collaboration skills. However, some research also indicates that if AI is not integrated within an appropriate pedagogical framework, it may restrict children's creative thinking abilities (Holmes et al., 2021). The data gathered suggests that, when supported by the right methods and tools, AI applications can enrich not only traditional classroom interaction but also individualized learning experiences. The comparative analysis of the main pedagogical findings from various studies is presented in Table 1, illustrating the multidimensional nature of the pedagogical impact area, evaluated in terms of both positive contributions and potential risks.

Table 1. Comparative summary of pedagogical contributions, ethical considerations, and policy/strategic ımplications of artificial ıntelligence applications in early childhood education (N=37)

Research	Method / Application Used	Pedagogical Findings	Ethical Findings	Policy/Social Strategic Implications
Aslan et al. (2024)	Multimodal, speech-based AI applications; case study	Personalized learning experiences; interactive and game-based approaches	Data privacy risks; need for greater attention to children's privacy	Innovative teacher training programs; strengthening digital infrastructure
Atabey& Scarff (2023)	Theoretical analysis; focus on the principle of justice	Emphasizes the importance of integrating fairness in educational settings	Ethical standards and regulatory framework recommendations for children's rights	Development of regulatory frameworks; policy recommendations
Berson et al. (2023)	Multimodal creative inquiry approach	Enhancing cognitive and creative processes; enriching learning experiences	Protection of children's data; ethical guidance for fair AI use	Development of ethical standards in education
Bielova & Byelov (2023)	Review; critique of children's rights and AI development	Highlights the need for careful consideration in innovative educational applications	Risks associated with algorithmic bias and lack of fairness	Emphasis on equality and transparency principles
Charisi et al. (2020)	Research; model promoting critical reflection	Supports children's development of critical thinking through AI and robotics	Need for ethical awareness in the use of technology	Ethical integration recommendations in education policies

Chu (2022)	In-depth analysis of ethical issues	Discusses AI’s role in education and its integration	Proposes the development and implementation of ethical standards	Recommendations for regulatory and ethical frameworks
Druga et al. (2019)	Experimental study; inclusive AI literacy approach	Supports the early learning of AI concepts	Emphasis on inclusive education policies and ethical frameworks	Policy recommendations for practitioners
Durrani et al. (2024)	Scoping review	Outlines the general framework of AI applications in early childhood education	Summarizes ethical and technical challenges encountered in practice	Development of regulatory mechanisms
Familyarskaya (2024)	Case analysis; practical application example	AI-supported learning models in preschool settings	Warnings on technological inequality, data security, and privacy	Local-level policy recommendations; regulatory approaches
Honghu et al. (2024)	Systematic evaluation of AI tools and technological infrastructure	Innovative learning approaches; focus on children's cognitive and linguistic development	Algorithmic bias; need for fair access and transparency	Identification of innovative integration strategies in education policies
Jin, L. (2019)	Experimental application; exploration of AI potential	Support for discovery-based learning models; enrichment of learning processes	Systematic measures for child data security and privacy	Development of school-based implementation models; local policy recommendations
Kahila et al. (2024)	Development of pedagogical framework	Promotes children's data agency and creativity	Ethical data use; importance of digital rights and security	Digital equity and innovative curriculum proposals
Kanders et al. (2024)	Perspective study; effects of generative AI	Evaluates generative AI’s contributions to learning in early education	Ethical boundaries; recommendations for regulations and implementation standards	Development of regulatory frameworks and policy recommendations
Kewalramani et al. (2021)	Experimental study; robotic toy applications	Supports social and emotional development; interaction-enhancing pedagogical applications	Privacy, data protection, and security concerns	Parent-teacher collaboration; establishment of regulatory mechanisms
Lian (2024)	Application analysis; ChatGPT-focused model	Contributions to designing interactive and supportive learning environments	Discussions on AI limitations, security, and ethical use	Regulatory dimensions of technological integration
Liu & Kromer (2019)	Methodological review; evaluation of AI-based tools	Encourages problem-solving, creativity, and critical thinking skills	Secure online interactions; implementation of data management standards	Curriculum integration; importance of educator guidance and strategic planning
Liu (2024)	Ethical research; evaluation of AI education systems	Highlights the importance of child-centered AI educational approaches	Ethical guidance, regulatory standards, and implementation strategies	Strengthening ethical standards in education
Masturoh et al. (2024)	AI-supported digital games and activities	Supports cognitive and social development through game-based learning environments; promotes digital literacy	Digital data management; focus on online security and privacy	Strengthening teacher-parent collaboration strategies; expansion of game-based instructional models

Mitchell et al. (2024)	Robot theater in informal learning environments	Raises awareness of AI and robotics ethics	Ethical AI design; development of implementation standards	Recommendations for regulatory and ethical frameworks
Ng et al. (2022b)	AI literacy curriculum design	Proposes curricula for early AI education	Emphasis on digital equity; ethical education approaches and policy recommendations	Curriculum integration; improvement of digital competence
Okeke (2022)	Case study; AI in professional preschool education	Example of teacher digital transformation practices	Findings on digital transformation and ethical practices in education	Policy reforms; local implementation models
Review on AI & Robots (2022)	Literature review (STEAM-focused)	Summarizes pedagogical contributions of AI and robotics integration	Application risks; ethical concerns; recommendations for regulatory frameworks	Development of regulatory frameworks and policy recommendations
Salloum (2024)	Ethical analysis	Discusses risks and opportunities of AI in educational environments	Importance of developing security, privacy, and ethical standards	Implementation of ethical educational policies and regulatory measures
Samara & Kotsis (2024)	Case study; AI use in science education	Proposes innovative AI-supported teaching methods in science education	Need for security and ethical implementation measures	Recommendations for technological integration and regulatory frameworks
Sharma et al. (2022)	Ethical call; analysis of AI interaction with children	Strategic approaches for AI integration into learning	Ethical AI design; protection of children’s rights; safe usage	Policy recommendations for the establishment of ethical standards in education
Sharma et al. (2023)	Ethical design and implementation research	Pedagogical recommendations for responsible AI applications	Child safety; fair use; establishment of ethical standards	Development of regulatory frameworks and policy reforms
Shawky et al. (2023)	Comprehensive ethical evaluation	Discusses the role of pedagogical approaches in AI use in education	Data security; regulatory gaps; ethical concerns	Strengthening ethical and regulatory measures
Siraj-Blatchford (2023)	Perspective article	Evaluates AI’s transformative potential in early childhood education	Equality, transparency, and accountability principles	Policy recommendations; regulatory approaches
Solichah & Shofiah (2024)	Scoping review	Identifies pedagogical models for fostering AI literacy in early childhood	Need for the establishment of ethical guidelines and data protection standards	Multi-stakeholder policy approaches; development of comprehensive curriculum recommendations
Su & Yang (2022)	Scoping review	Provides a general framework for AI applications in early childhood education	Ethical and technical challenges in implementation	Development of innovative regulatory mechanisms
Su & Zhong (2022)	Curriculum design research	Proposes AI-based educational programs	Establishment of regulatory frameworks and ethical standards	Curriculum integration; emphasis on policy reforms
Su et al. (2023)	Literature analysis	Evaluates AI literacy approaches in early education	Recommendations for fair and ethical AI applications	Comprehensive recommendations for education policies

Su et al. (2024)	Experimental study; cooperative game and direct instruction models	Supports cognitive, computational, and social skills in kindergarten	Emphasis on data security, privacy, and teacher digital competencies	Integration into early education curricula; strengthening teacher digital competencies; policy reforms
Tazume et al. (2020)	Multi-modal interactive AI robot applications	Contributes to the enrichment of interactive learning processes	Importance of security, privacy, and ethical awareness	Recommendations for regulatory and ethical frameworks
Williams et al. (2019)	Curriculum design; pilot implementation	AI-supported learning environment design and implementation	Ethical dimensions of technological integration	Regulatory recommendations; implementation strategies
Yang (2022)	Theoretical analysis; curriculum recommendations	Discusses why, what, and how AI education should be taught	Need for curriculum reform and establishment of ethical standards	Innovative curriculum proposals; policy reforms
Yusof et al. (2024)	Application analysis; generative AI-supported model	Supports AI integration into teacher education	Security, transparency, and accountability-based policy recommendations	Technological integration; regulatory policy recommendations

Table 1 summarizes the research focus and contributions of thirty-seven studies directly related to the main areas of the study: pedagogical paradigms, ethical issues, and policy/strategic recommendations. The methods and findings of each study are addressed in a way that reveals the multidimensional effects of AI applications in early childhood education. AI-supported tools and applications are seen to offer potential benefits in developing children's cognitive and social skills. However, more research is needed regarding the limitations and long-term effects of these applications. These findings indicate that the integration of AI in early childhood education presents both opportunities and points that need careful consideration. Educators and policymakers must implement a thoughtful planning and execution process to ensure the effective and ethical use of these technologies. The pedagogical opportunities, ethical responsibilities, and strategic policy requirements offered by AI applications in education are reflected in a more comprehensive and detailed manner. The data gathered from both experimental and theoretical studies suggest that a multidimensional approach is needed for the successful integration of AI in early childhood education.

Ethical Issues

The findings regarding ethical issues, another significant dimension of the research, reveal that AI-based educational applications raise serious discussions about children's data privacy, security, and individual rights (see Table 1). Additionally, analyses by Livingstone and Stoilova (2020) emphasize that the collection and processing of personal data during the use of AI technologies at a young age present significant privacy and security risks. Similarly, researchers such as Borenstein and Howard (2021) have pointed out that observed biases in AI algorithms could lead to inequalities in educational opportunities, particularly having more significant outcomes for disadvantaged groups. In this context, the lack of ethical guidelines and regulatory frameworks increases the potential risks of AI systems, while also raising questions about the reliability and inclusiveness of these applications. Based on the findings, some studies offer recommendations for the establishment of ethical standards and regulatory mechanisms. However, they also reveal ongoing uncertainties regarding the scope and impact of these proposals (see Table 1). This situation introduces risk factors that could deepen the digital divide in education, especially in low-income areas and schools lacking technological infrastructure.

The use of AI applications in early childhood education brings significant ethical issues such as data privacy, algorithmic bias, and children's privacy. Studies stress the need for transparency and security standards during the collection and processing of children's personal data. Researchers such as Akhtar et al. (2023), Borenstein & Howard (2021) and Liu (2024) argue that algorithmic biases and the misuse of digital tools increase the risk of creating inequality and injustice in education. This demonstrates the inevitability of establishing child-centered ethical frameworks for AI applications targeted at early childhood.

Policy, Social, and Strategic Orientations

From a policy perspective, international organizations (such as OECD, UNESCO) and experimental applications highlight the need for multi-stakeholder strategies to ensure that AI integration in early childhood education is sustainable and inclusive. The study by Su et al. (2024) argues that cooperative games and direct teaching models should be applied in parallel with curriculum reforms to enhance teachers' digital competencies. Policymakers should focus on creating regulatory mechanisms based on transparency and accountability that strengthen teacher-parent collaboration.

Analyses of policy and strategic orientations reveal the necessity of comprehensive and multi-stakeholder strategies for the successful integration of AI in early childhood education. Reports published by international organizations, particularly those from OECD, UNESCO, and the European Commission, indicate the need for the development of new regulatory frameworks to effectively use AI technologies in education. A pilot study by Zhao et al. (2022) showed positive results from AI-supported educational applications, yet significant gaps remained in teacher training and digital literacy. These findings suggest that policymakers should prioritize strategic planning to maximize the potential benefits of AI technologies in education while minimizing inequalities and ethical risks during the widespread adoption of these technologies.

Overall Trends in Scientific Research on the Integration of AI in ECE

The integration of artificial intelligence (AI) into early childhood education presents both pedagogical opportunities and ethical considerations. This graphic (Figure 3) provides a structured analysis of AI's pedagogical benefits, ethical risks, and associated pedagogical models based on the related literature review.

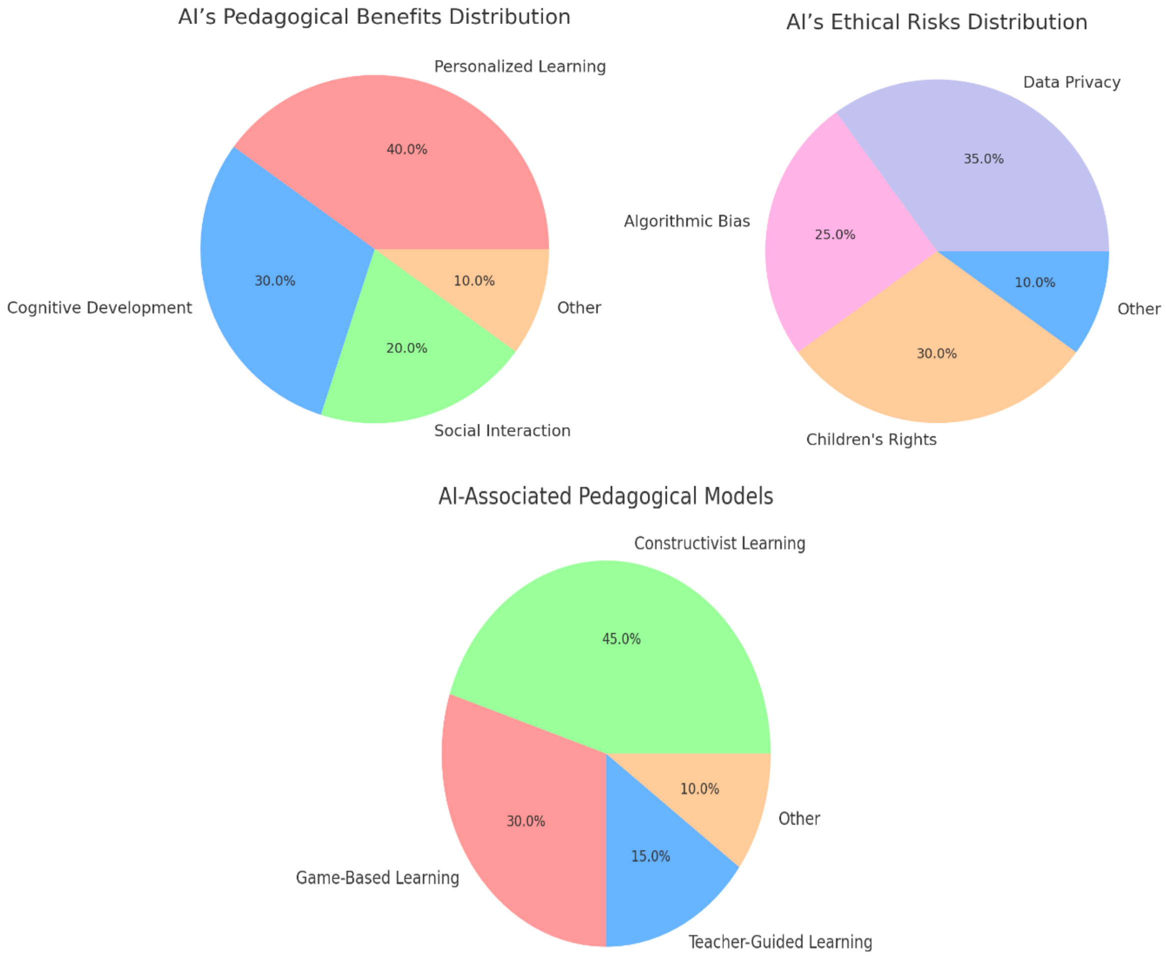

Figure 3. The role of artificial intelligence in early childhood education: pedagogical benefits, ethical risks, and associated learning models

AI-driven educational technologies contribute significantly to early childhood learning experiences. The distribution of AI's pedagogical benefits reveals that personalized learning (40%) is the most recognized advantage, as AI enables tailored educational pathways that adapt to individual students' needs. Cognitive development (30%) is another key benefit, as AI-assisted tools enhance problem-solving abilities and critical thinking. Furthermore, social interaction (20%) is supported through AI-driven interactive learning environments, such as robot-assisted education and adaptive learning systems. However, other benefits (10%), such as engagement in digital literacy and improved motivation, are also noted in the literature.

Despite its potential benefits, AI in education raises serious ethical concerns. The most prominent issue is data privacy (35%), as AI-based systems collect and process large amounts of personal data, raising questions about security and child protection. Algorithmic bias (25%) is another critical risk, as AI models trained on biased datasets may reinforce existing inequalities in education. Children's rights (30%) are also a major concern, particularly regarding consent, autonomy, and fair access to AI-driven learning tools. Additionally, other ethical risks (10%), such as digital dependency and the diminishing role of human teachers, require further investigation.

The adoption of AI in early childhood education aligns with various pedagogical models. The findings suggest that constructivist learning (45%) is the most frequently associated model, emphasizing active exploration and discovery-based learning. Game-based learning (30%) is another prominent approach, leveraging AI to create immersive and interactive educational experiences. Teacher-guided learning (15%) highlights the role of AI as a supportive tool rather than a replacement for human educators. Finally, other models (10%), including hybrid approaches that combine AI-driven and traditional methods, are emerging in educational research.

To sum up, the findings indicate that, in addition to the pedagogical opportunities AI offers in early childhood education, there are many important ethical and policy issues that need to be carefully considered. From a pedagogical perspective, AI-supported learning environments contribute positively to children's cognitive, linguistic, and social development by providing individualized learning experiences. However, these technologies could also have restrictive effects on fundamental skills like creative thinking and originality if not integrated into an appropriate pedagogical framework. From an ethical standpoint, issues such as data privacy, algorithmic bias, and digital inequality have become even more critical with the widespread use of AI applications. In this context, the establishment of regulatory and ethical guidelines has become necessary. From a policy perspective, strategic models developed at both national and international levels reveal that the pedagogical and ethical dimensions of AI integration must be addressed integrally. These findings lay the foundation for further research and policy recommendations and emphasize the need for multidisciplinary approaches to ensure that AI technologies are used more effectively and fairly in early childhood education.

Discussion and Conclusion

The use of artificial intelligence (AI) in education has multifaceted effects, particularly in early childhood education, a delicate and crucial developmental stage. This study comprehensively examines how AI can be integrated into pedagogical practices, the ethical risks associated with it, and how educational policies should be shaped in response. The findings suggest that while AI has the potential to enrich learning processes in early childhood education, it also raises significant ethical and strategic questions.

Jean Piaget's cognitive development theory (1952) emphasizes the importance of children actively interacting with their environment during the learning process. AI-supported learning environments offer personalized experiences that allow children to progress at their own pace and deepen their exploration processes. This presents a significant opportunity, particularly for children with learning differences. AI-based educational platforms can adapt to children's learning styles and provide personalized content, making education more inclusive. However, a key point is that AI should not only be viewed as a tool but also as a complementary and supportive element in pedagogical processes.

On the other hand, Lev Vygotsky's social interaction theory (1978) suggests that the potential effects of AI on children's social development need careful consideration. Vygotsky posits that peer interaction and teacher guidance play critical roles in cognitive development. Therefore, a key research question is how AI-supported learning environments shape children's interactions with teachers and peers. While there are positive findings suggesting that robot-assisted educational tools can enhance social interaction skills (Kewalramani et al., 2021), it is also crucial to be cautious about AI potentially distancing children from human-centered learning experiences.

From the perspective of Bronfenbrenner's Ecological Systems Theory (1979), AI's transformation of interactions among children, teachers, parents, and policymakers is also an important aspect. AI-based educational tools directly impact children's learning processes while redefining teachers' pedagogical roles and altering parents' roles in education. In this context, teachers' and parents' digital literacy significantly influences children's interactions with AI. Findings indicate that teachers require more guidance on how to use AI-supported educational materials in the classroom, and parents have concerns regarding data security and digital addiction.
Ethically and in terms of data privacy, the findings underscore the need to address issues such as algorithmic bias, data security, and privacy to fully harness AI's potential in education. Protecting children's personal data and making the decision-making mechanisms of AI-based systems transparent continue to be among the biggest debates in educational AI (Berson et al., 2023; Bielova & Byelov, 2023). While AI in education can promote equality of opportunity, it also risks deepening socioeconomic disparities. In areas with limited access, the opportunities offered by AI-supported education become harder to utilize, exacerbating the digital divide.

Another area of debate is the long-term impact of AI on pedagogical approaches. The tension between behaviorist and constructivist approaches in education is reshaped in the context of AI integration. Some AI-supported systems may encourage children to learn within specific patterns, potentially limiting the exploration and experiential learning processes offered by constructivist environments. This raises the question of which pedagogical frameworks AI in education aligns with. Will AI lead children toward rote learning, or will it support discovery-based learning?

AI systems in education are increasingly supporting children's learning processes. However, their potential to reinforce societal biases cannot be overlooked. Since AI algorithms are trained on large data sets, biases present in these data can be directly reflected in the models. For example, AI-based educational tools may incorporate biases related to gender or ethnicity, disadvantaging certain student groups. Additionally, human moderators' conscious or unconscious biases in data labeling can influence decisions on what content is deemed appropriate. This can lead to educational materials being shaped by specific perspectives, potentially hindering children's development of critical thinking skills.

From a pedagogical standpoint, while AI systems offer personalized learning opportunities, they also present risks. Students encountering only algorithm-driven content may experience negative effects on their social interaction skills and cognitive flexibility. Furthermore, excessive reliance on AI could weaken students' problem-solving and critical thinking abilities. Therefore, it is essential to integrate AI into education in line with ethical principles, ensuring algorithmic transparency and increasing data diversity. When designing AI systems for children, a balanced approach to pedagogical strategies is necessary to create policies that minimize biases and promote equality of opportunity in education.

The findings also indicate that educational policies must adapt to this transformation. At both the national and international levels, education policies must encompass multidimensional changes, from teacher training to curriculum reforms, digital infrastructure investments, and data security regulations. The success of AI-supported educational systems depends not only on strengthening technological infrastructure but also on teachers' ability to integrate these tools into pedagogical processes. Therefore, policymakers must support the use of AI through teacher training, ethical regulations, and curriculum reforms.

To sum up, the integration of AI into early childhood education is a complex and multilayered process that affects all components of the education system. AI-supported learning systems offer personalized learning opportunities and pedagogical innovations but also bring significant ethical and policy-related challenges. In line with Piaget, Vygotsky, and Bronfenbrenner's theoretical frameworks, AI holds great potential as a tool to support cognitive development, but it cannot fully replace the human-centered nature of pedagogical processes. Therefore, how AI is positioned in education, the pedagogical and ethical principles guiding its use, and how it is supported through teacher-parent collaboration remain critical questions.

This study provides a comprehensive framework for how AI can be more effectively and responsibly integrated into early childhood education, offering valuable contributions to the literature. The findings provide a solid foundation for further empirical research on the long-term effects of AI integration into educational processes, which is critical for policymakers and practitioners. The role of AI in education is not merely a technological transformation but also a critical factor that reshapes the future educational paradigm, encompassing pedagogical, ethical, and policy dimensions. At this point, the proposed model offers a multidimensional approach to the integration of artificial intelligence (AI) in early childhood education, distinguishing itself from existing AI-based educational frameworks.

Unlike previous models that primarily focus on personalized learning (Chen et al., 2020) or technology-enhanced teaching strategies (Luckin et al., 2016), this model holistically incorporates pedagogical paradigms, ethical concerns, and policy frameworks into a unified structure. By integrating Piaget's discovery-based learning, Vygotsky's social interaction model, and Bronfenbrenner's ecological systems theory, it ensures that AI applications not only support cognitive development but also enhance social and emotional learning through interactive and play-based environments. Moreover, while existing models often consider ethical and data privacy concerns as secondary issues, this study places child rights, algorithmic bias, and AI-driven educational inequalities at the forefront of its analysis. Additionally, the model moves beyond a technocentric perspective, offering strategic policy recommendations that address teacher training, regulatory frameworks, and the accessibility of AI-enhanced education. This comprehensive integration of pedagogical, ethical, and policy dimensions makes it one of the first AI models specifically tailored to early childhood education, ensuring a human-centered, inclusive, and developmentally appropriate approach to AI implementation in educational settings.

Recommendations

This study not only highlights the pedagogical opportunities that artificial intelligence (AI) offers in early childhood education but also reveals the risks it may pose in ethical and political dimensions. Researchers should undertake comprehensive empirical studies to assess the long-term effects of AI on children's cognitive, social, and emotional development. At the same time, they should develop theoretical and practical models that will ensure the integration of this technology in a way that supports personalized learning experiences while preserving human-centered educational values. Educators, in turn, should create continuous professional development programs focused on digital literacy and AI-based pedagogical approaches, exploring ways to use technology effectively and ethically in the classroom. Furthermore, addressing fundamental ethical issues such as data security, algorithmic bias, and children's privacy requires the creation of regulatory frameworks based on interdisciplinary collaboration, valid both locally and internationally. Thus, by supporting AI applications in early childhood education with comprehensive policy reforms, teacher-parent collaborations, and ethical standards, it will be possible to create a sustainable and inclusive learning environment that contributes to children's development.

The findings of this study reveal the potential of AI to enrich personalized learning experiences in early childhood education and positively impact children's cognitive, linguistic, and social development. However, they also provide important warnings regarding data privacy, algorithmic bias, and the importance of human-centered interactions. In this context, future research should empirically examine the long-term effects of AI applications, thoroughly assessing the opportunities and risks presented by the technology. It is crucial that educators, when adopting AI-based pedagogical models, also incorporate approaches that support in-class human interaction and critical thinking. Additionally, teachers' professional development in digital literacy and AI integration is a key element for ensuring that applications are used effectively and within ethical boundaries. Collaboration between policymakers and researchers to establish regulatory frameworks that include data security, algorithmic transparency, and child-centered ethical standards will be an essential step in realizing the potential of AI in early childhood education in a sustainable and inclusive way.

The results of the study show that AI applications support personalized learning experiences in early childhood but cannot replace social interaction and guidance in children's natural developmental processes. In this context, considering Piaget's emphasis on active exploration and learning through experience, Vygotsky's focus on social interaction and teacher guidance, and Bronfenbrenner's approach to evaluating children's development in the context of environmental interactions, AI-supported systems should be designed to allow children to learn at their own pace while also enriching teacher and peer interactions. This recommendation will contribute to creating child-centered, ethically aligned educational environments that integrate the personalized learning opportunities provided by AI with children's cognitive, emotional, and social development. Thus, technological applications can be used as complementary tools that support children's exploration, critical thinking, and social interaction skills, rather than interfering with their natural developmental processes.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the author.

Funding Declaration

The author did not receive support from any organization for the submitted work.

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Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025 https://doi.org/10.55549/jeseh.785

Gifted Students' Perceptions of Artificial Intelligence through Drawings: A Perspective from Science and Art Centers

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Article Info

Article History

Published:
01 April 2025

Received:
10 January 2025

Accepted:
22 March 2025

Keywords

Gifted students,
Artificial intelligence (AI),
Human-machine relationships,

Abstract

Artificial Intelligence (AI) emerges as the development of computer systems and software that imitate human abilities and perform human-like tasks. Understanding what gifted students think about this system that includes deep cognitive abilities is considered important. Based on this premise, this study examines the perceptions of gifted students towards the concept of AI. The research was conducted using phenomenological design, a qualitative research method. The data of the research were collected from 50 gifted students enrolled at a Science and Art Center and selected through a convenience sampling method. The "Draw-Write" form was used as the data collection tool. The data obtained were analyzed using content analysis, consistent with the nature of qualitative research methods. The study shows that participants may have three types of positive, neutral and negative roles related to AI. The research findings suggest that gifted students perceive AI as both a supportive tool and a potential competitor to human capabilities. The research showed the need for ethical considerations and awareness of the societal impacts of AI. Their futuristic vision shows that they are ready to explore the potential applications of AI in various fields. By recognising and addressing these perspectives, educators and policy makers can foster an environment that balances innovation with ethical responsibility and enables AI to serve as a tool for collective progress.

Introduction

Artificial Intelligence (AI) has emerged as one of the most significant technologies of the future, creating a profound impact in the scientific and technological domains in recent years. AI is defined as a set of algorithms and systems developed to enable machines to perform human-like tasks and includes processes that simulate human intelligence (Russell & Norvig, 2016; Isler & Kılınc, 2021). This technology not only performs complex processes such as data analysis, learning, problem-solving, and decision-making but also adapts to dynamic conditions by learning and improving from the data it receives.

Today, AI is revolutionizing sectors such as healthcare, education, finance, and manufacturing, profoundly transforming the operations within these fields (Kaplan & Haenlein, 2019). From diagnosis and treatment processes in healthcare to risk management and data analysis in finance, from personalized learning environments in education to automation in manufacturing, AI offers transformative innovations across a wide range of applications. The potential of AI in the field of education is equally expansive. This technology has the potential to reshape educational environments with adaptable learning systems in line with educational management, student success tracking, and individual learning needs (Holmes et al., 2019; Arslan, 2020). With the power of big data analytics, it is now possible to create personalized educational experiences that adapt to each student's unique learning pace and style. These AI-supported learning systems offer a powerful tool to better understand students' needs and shape educational processes accordingly (Arslan, 2020; Kocyiit & Darı, 2023; Tekin, 2023).

However, the incorporation of AI into education also necessitates an evaluation of societal and individual perceptions and attitudes towards this new technology. Examining how students perceive AI is crucial for understanding the societal integration and acceptance of this technology (West & Allen, 2020). Learning about the social acceptance of artificial intelligence and its potential future areas of use is possible by understanding individuals' perceptions of this technology (Pirim, 2006). In this context, the variability in perspectives towards AI based on age and cognitive abilities necessitates the analysis of different demographic groups' viewpoints. Particularly, individuals with advanced creative and critical thinking skills, such as gifted students, hold significant importance in this regard. Gifted individuals, known for their abstract and analytical thinking skills, tend to be more sensitive to technological advancements and are inclined to critically analyze these developments (Renzulli, 2012). Often, their unique perspectives on innovations and complex issues enhance their potential to comprehend societal advancements. Therefore, examining gifted students' perceptions of AI can provide valuable insights into how they might interact with this technology in the future. The critical perspective of gifted students can be decisive both in the evaluations of the social effects of AI and in the acceptance of this technology in society.

The way this group of students perceives AI can be analyzed across a broad spectrum. The concept of AI can be interpreted by students from utilitarian, critical, or futuristic standpoints. Some perceive AI as a tool that supports humans and enhances quality of life, while others view it as a competitive force or a technology capable of disrupting societal order (Bostrom, 2016). As highlighted in the literature, while some individuals see AI as a beneficial support for humanity, others consider it a potential threat. Among gifted students, there is often an awareness of the potential dangers of AI, coupled with both positive and negative perspectives towards this technology. In education, AI's potential role can be perceived as a factor encouraging students to seek more interactive and suitable solutions for learning processes (Brynjolfsson & McAfee, 2014).

The perceptions of gifted students regarding AI serve as significant indicators of how societal acceptance of this technology might evolve. Their perspectives not only shed light on the impacts of AI in education or the workplace but also offer insights into how AI will be accepted by society in the future (Siau & Wang, 2020; Keskin & Ozkan, 2022). The purpose of this study is to gain an in-depth understanding of the perceptions of gifted students towards AI and to evaluate the potential implications of these perceptions for the societal integration of AI technology. Understanding how young individuals evaluate AI from different perspectives can contribute to the more conscious and beneficial application of AI in education and other sectors.

Purpose of the Study

The primary purpose of this study is to explore the perceptions of gifted students towards the concept of artificial intelligence (AI). Investigating these perceptions not only helps to understand their thoughts on this technology but also provides significant insights into the societal acceptance and impact of future technological advancements. In this context, the study seeks to answer the research question: *"What are the perceptions of gifted students towards the concept of artificial intelligence?"*

Method

Research Design

The study was conducted using phenomenological design, a qualitative research method. This approach aims to analyze in detail how individuals experience and interpret a phenomenon. Phenomenological research focuses on the shared meaning of lived experiences related to a phenomenon or concept (Creswell, 2013). In this study, the phenomenon of interest is the concept of artificial intelligence. Thus, the primary focus of this research is to investigate how gifted students understand, interpret, and conceptualize AI.

Participants

The data for the study were collected during the fall semester of the 2024-2025 academic year from 50 gifted students enrolled at the Science and Art Center (SAC), selected through convenience sampling. The demographic characteristics of the participants are presented in Table 1.

Table 1. Demographic characteristics of the participants

Groups	Number of Students	Female	Male
Support	27	13	14
ITR	14	8	6
STD	7	4	3
Project	2	1	1
Total	**50**	**26**	**24**

When the demographic characteristics of the 50 students in the study group are examined, it is seen that 26 are girls and 24 are boys. These students are divided into four groups based on their individual needs and talents: "Support", "Individual Talent Recognition" (ITR), "Special Talent Development" (STD), and "Project" groups. Students continue their education at SAC in different groups according to their individual needs and talents. The Support group comprises students aged 7-12 who require guidance in developing basic skills in specific areas. The ITR group focuses on helping students aged 9-14 discover their potential and build self-confidence by recognizing their strengths.

The STD group supports students aged 10-16 with specific talents to advance their abilities to a higher level. Finally, the Project group involves students aged 12-18 conducting research on a specific subject and produce concrete outputs in order to foster problem-solving, collaboration and creativity skills. Among the groups, the Support group includes 27 students (13 female, 14 male); the ITR group consists of 14 students (8 female, 6 male); the STD group includes 7 students (4 female, 3 male); and the Project group comprises 2 students (1 female, 1 male).

Data Collection Tool

The "Draw-Write" form, developed by the researchers, was used as the data collection tool. The Draw-Write Form is a creative data collection tool used in the study and aims to deeply examine individuals' perceptions of the concept of artificial intelligence. This form allows participants to express their thoughts both visually and in writing. In alignment with the phenomenological design of qualitative research, this form allows participants to visualize their ideas about AI through drawings and provide written explanations. Having students concretize their thoughts about artificial intelligence with a picture over a certain period of time is a valuable method in terms of revealing their mental images and emotional reactions to this concept. The written explanations provided after the drawings allow participants to express their perceptions in more depth, while also revealing their relationship with this concept and their experiences more clearly. This dual-phase process facilitates a multidimensional evaluation of gifted students' perceptions of AI, contributing to the overall aim of the study. Thus, it became possible to obtain important findings on how students interpret the concept of artificial intelligence and the social acceptance of this technology. Participants were given 30 minutes to complete their drawings and provide written descriptions without any restrictions.

Data Analysis

The drawings and written explanations provided by the participants were analyzed using the content analysis method, consistent with the nature of qualitative research. Content analysis systematically identifies themes and codes to understand participants' perceptions, emotional responses, and experiences with the concept of AI. During the analysis process, the themes and codes evident in the drawings were first identified based on the visual elements and content of the written descriptions. To ensure coding reliability, the analysis involved two independent researchers and a coding list. The reliability of the coding process was enhanced using the Miles and Huberman (1994) reliability formula, which calculated an agreement rate of 95% between the codes. This high consistency among researchers strengthened the quality and reliability of the analyses performed.

Findings

This study delves into the perceptions of gifted students regarding the concept of artificial intelligence (AI). The findings reflect participants' interactions with AI, their interpretation of this technology, and their perspectives on its role in education. Below, the main themes identified in the study and the corresponding participant insights are presented.

Human-Machine Interaction

It was determined that some students depicted the concept of human-machine interaction in their drawings. Selected drawings under this theme are presented in Figure 1.

Figure 1. Drawings by participants S12, S23, and S21.

Below are sample participant statements within this theme:

S14: "*The robot chip is the brain of the robot. This robot has a triangular head with a hole. It is a smart robot."*
S21: "*Artificial intelligence, although a machine, can think like a human brain or give the impression that it can think. AI prevents the loss of time related to a task and provides rapid answers to scientific questions."*
S27: *"AI makes human work easier. We interact with AI so much that it feels like it has become our world. We spend 24 hours with it. It has many benefits, but it could endanger our health, especially our eyesight. Thousands of disadvantages might emerge in the future."*

Students' drawings and explanations show that they associate AI with human-like thinking abilities, perceiving it as an intelligent entity. Based on the drawings and explanations of the students, it has been suggested that they define artificial intelligence as both functional and a structure close to humans.

Artificial Intelligence in Education

It was determined that some of the students created drawings emphasizing the increasing importance of the role of artificial intelligence technology in the education-teaching process. Some participant drawings within this theme are given in Figure 2.

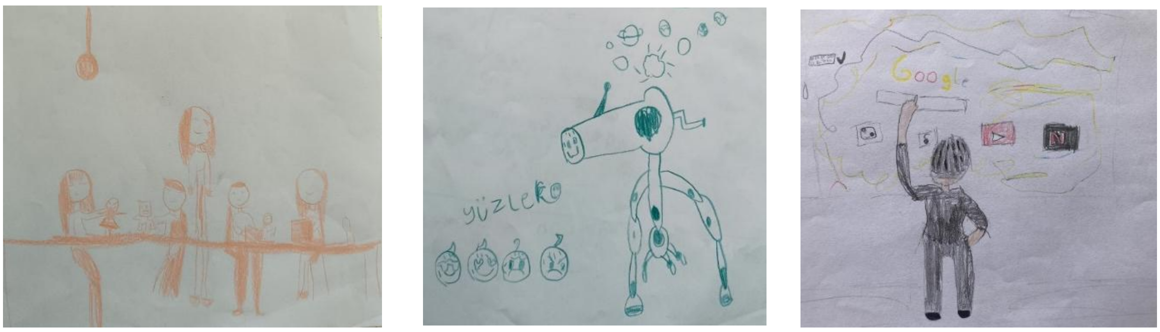

Figure 2. Drawings by participants S6, S47, S48,

Below are sample participant insights for this theme:

S6: *"Teachers often use smartboards in lessons. Smartboards are made with AI, similar to smartphones. They are touch-sensitive."*
S47: *"I find AI fascinating. This AI tool studies planets. You can select the planet you want to see, and it shows it to you."*
S48: *"In class, children build robots. They design different robots, and some upload the data into computers."*

Participants emphasized how AI has transformed educational environments by stating that teachers frequently use smart boards in classes and that these boards are equipped with artificial intelligence. Other students, on the other hand, emphasized the wide range of uses of AI in education and emphasized the impact of this technology on teaching processes with the statement, “We use AI a lot in education.” In addition, students drew attention to the interactive and entertaining aspects of AI; for example, one student (S47) stated that AI-supported vehicles have the ability to examine planets and that they were interested in these vehicles. This situation reveals the potential of AI to enrich the learning experience. In addition, students’ designing robots in classes provides a concrete example of the integration of AI into education. These findings reveal students' perceptions of AI as a cornerstone of innovative educational practices and its potential to enrich learning experiences.

Artificial Intelligence and Digital Integration

The theme of "AI and Digital Integration" reflects students' perceptions of AI’s interaction with technological devices. Selected drawings are shown in Figure 3.

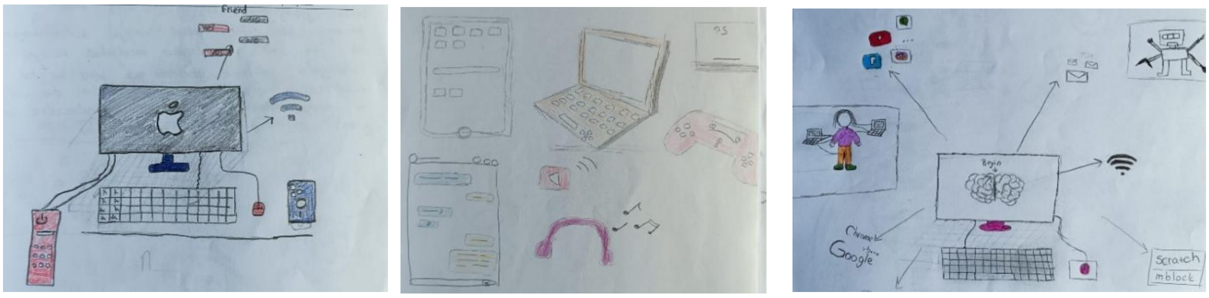

Figure 3. Drawings by participants S2, S31, S34, S31

Below are some participant statements related to this theme:

S2: *“In my opinion, Artificial Intelligence is electronic devices that are useful to humans. Also, robots are artificial intelligence tools: such as computers, robots and smartphones”*
S28: *“Almost every household has at least one technological device. Who makes these devices, and what are they for? Technological devices are created by AI, including phones, tablets, computers, and TVs.”*
S31*: “When I think of AI, technological devices such as programs (WhatsApp, YouTube, Instagram) and music come to mind.”*
S34: *“In this picture, the major role of the internet and technological devices in AI is depicted. Words such as phone, tablet, computer, internet, etc. remind me of artificial intelligence.”*

Some of the students defined artificial intelligence as an underlying concept of technological devices such as computers, smartphones, robots, and tablets. For instance, while one student (S2) stated that artificial intelligence is "electronic devices that are useful to people," another (S28) elaborated on the functionalities and conveniences offered by these devices. It was also emphasized that artificial intelligence provides information flow through media tools such as television. In their drawings and explanations, students provide examples of how artificial intelligence shapes their daily lives and draw attention to the role of this technology in the advancement of science and innovation. Students' thoughts on digital integration with artificial intelligence reveal the importance and impact of integrating this technology into individuals' lives.

Futuristic and Fantastic Visions

Figure 4. Drawings by participants S8, S46 and S25, respectively.

Some gifted students reflected their imagination by exploring AI's potential future applications, resulting in the theme "Futuristic and Fantastic Visions." Selected drawings under this theme are presented in Figure 4. Below are sample insights from participants:

S8: *"If a robot chef is invented, it will tell us what goes best with the food we eat. We don't always know what goes best with which food. Also, this artificial intelligence robot will tell us which drink goes best with the food."*
S18: *"Soon, we will live in space bases thanks to technology. I think it will be like living in the real world."*
S36: *"The cooking robot YEMİ. YEMİ helps elderly people. It buys their household needs from the market. After bringing it home, it asks the elderly what they want to eat and prepares it in an hour. In addition, the robot can connect to the technology and appliances in the house and control them. It can clean and wipe the house."*
S46: *"This thing I drew is a movie technology. What I drew has been in many Godzilla movies. This thing is a robot version of Godzilla and humans have cretaed it. This thing does not exist in reality. Its name is Mechgodzilla."*

Some of the participants stated that artificial intelligence can not only make daily life easier but also offer innovative solutions that can transform human life. For instance, a chef robot designed by a student (S8) will be able to optimize decision-making processes in the kitchen by determining which drink would be more suitable with meals. In addition, another student (S18) imagines the evolution of technology by suggesting the idea of living in space bases. In the students' explanations, it is noteworthy that with the integration of robots into human life, they imagine artificial intelligence-supported systems that help the elderly, take on housework and provide health services. Some students emphasize the elements of science fiction, bridging the gap between the real world and fantasy through the influence of futuristic robots and technological devices in popular culture and their place in the imagination. These futuristic and imaginative perspectives highlight students' capacity to view AI not just as a current technology but as a domain full of potential for reshaping human life in the future.

Fear, Power, Threat and Control Dynamics

The theme of "Fear, Power, Threat, and Control Dynamics" highlights the focus of gifted students on the potential dangers and power dynamics associated with artificial intelligence. Some student drawings reflecting this theme are presented in Figure 5.

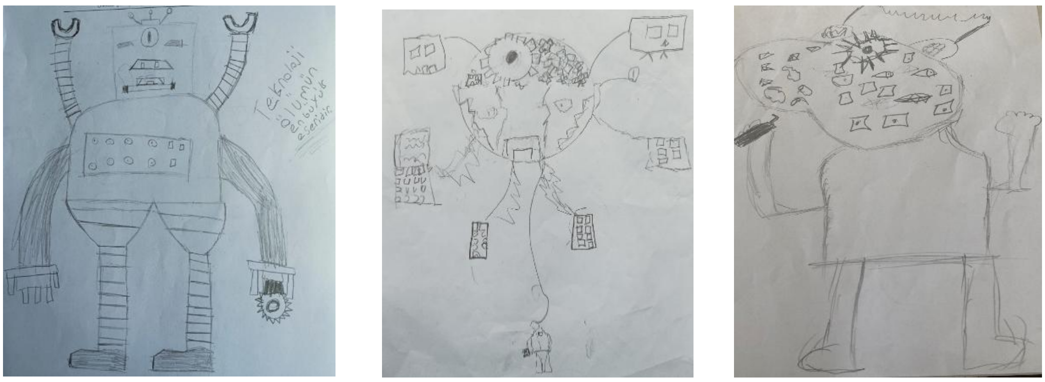

Figure 5. Drawings by participants S3, S13, and S5

The following are selected student statements related to this theme:

S2: *"I think it's good to have artificial intelligence, but if there are robots with their own will, they might harm us."*
S3: *"Artificial intelligence technology is the greatest work of death."*
S5*: "This is Woden. He is an artificial intelligence robot. He competes with the smartest people. People underestimate him at first, but when he defeats them, they give up. When someone powerful comes, he makes him passive. "*
S13*: "This robot produced by artificial intelligence has become very powerful. This tablet, computer, TikTok has taken control of us all."*
S26: *"Robots replacing humans and acting as they wished, and as a result, humans will disappear."*
S34: *"If artificial intelligence is being misused by humans even now, artificial intelligence could become very bad in the future."*

In their drawings and explanations, some students express concerns that artificial intelligence could pose a threat to humanity and emphasize fears such as loss of control in this context. For example, while some students fear that people will lose their jobs as a result of the misuse of artificial intelligence, others think that the rapid development of technology could jeopardize control over human life. Students have embodied their thoughts that artificial intelligence could change the balance of power and gain superiority over humanity in their drawings and explanations. Feelings of fear and threat arise strongly in response to the uncertainties and possible negative outcomes associated with AI. At the same time, the students' willingness to question and discuss the relationship between artificial intelligence and humans plays an important role in shaping social perception on this issue in the future.

Artificial Intelligence and Robotic Systems

The theme of "Artificial Intelligence and Robotic Systems" reflects gifted students' perceptions and expectations regarding the relationship between AI and robotics. In this context, some of their drawings are presented in Figure 6.

Figure 6. Drawings by participants S1, S15 and S19

The following are selected student statements related to this theme:

S1: *"Artificial intelligence makes me operate these devices. I think there is a connection between them. That's why I drew something like this. Robots are becoming indispensable in our lives."*
S15: *"A faucet that works with solar energy. It transmits the "operate" command from the energy cables to the cables and operates the faucets."*
S20: *Home lighting system: They allow us to do many things from a single place, such as the temperature of the house, the lights and many other things. For example, if you tell this device to turn on the room light from where we are sitting, it turns on the room light. The negative aspect is that you will not be able to even stand up anymore, so you will not be able to do sports and as a result, we may encounter many diseases."*
S32: *"When I say artificial intelligence, I immediately think of very smart robots."*
S50: *"My robots do everything. They make pizza, do homework, and a head robot watches them. It manages them and its name is Pokemonrobo."*

Some participants emphasized the influence of AI on robotic systems, showcasing how these systems provide convenience and functionality in daily life. For instance, students highlighted the ability of robots to perform various tasks efficiently, emphasizing the speed and productivity AI enables. Additionally, as S50 describes, students' imaginative robots are envisioned to handle complex tasks alongside routine ones. In this context, these depictions and explanations reveal a comprehensive consideration of AI and robotic systems' societal impact, highlighting their potential benefits as well as their associated risks.

Artificial Intelligence and Games

The theme of "Artificial Intelligence and Games" shows that students reflect different perceptions and experiences of the role of artificial intelligence in the game world. Drawings created by some students within this theme are given in Figure 7. The following are selected student statements related to this theme:

S11: *"Someone named Herobrine has superior characteristics. While making fun of the baby zombie, the baby zombie created a golden armor and they both respect each other. Thus, they become friends forever."*
S17: *"This child named Zeynep is wearing virtual reality glasses and playing a game. At that moment, it starts to rain. Zeynep is standing under a tree. Her friends are calling her but Zeynep doesn't even hear."*

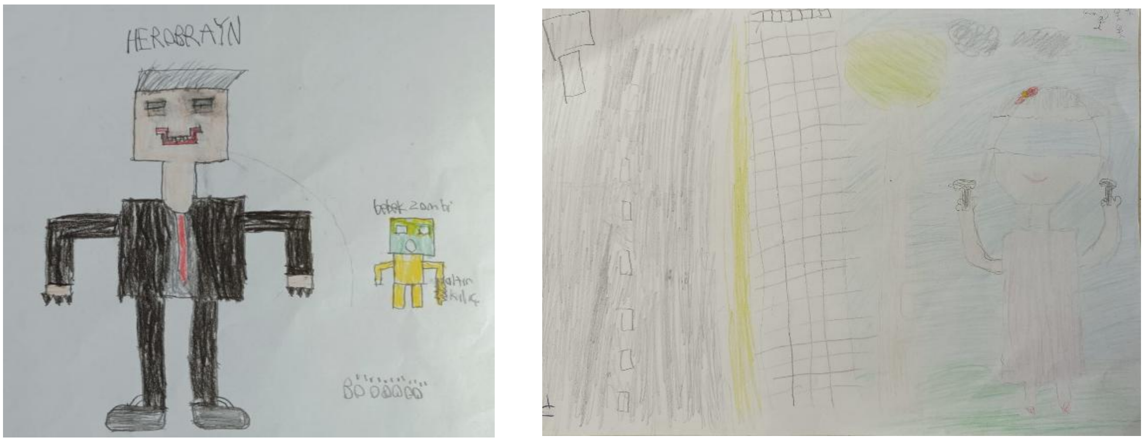

Figure 7. Drawings by participants S11 and S17.

The students' explanations within the scope of the theme "Artificial Intelligence and Games" reveal the impact of this technology on gaming experiences and the interaction between the virtual world and reality. For instance, S11's description demonstrates how AI enhances character interactions within games and the bonds players form with these characters. On the other hand, S17 illustrates the potential consequences of immersive virtual reality technology, such as social disconnection and the neglect of real-world interactions. These insights underscore concerns about how virtual games might weaken social bonds among players

Artificial Intelligence and the Development of Humanity

The students' opinions on the theme "Artificial Intelligence and the Development of Humanity" emphasize the broad impacts of artificial intelligence on society and the individual. Selected drawings are presented in Figure 8.

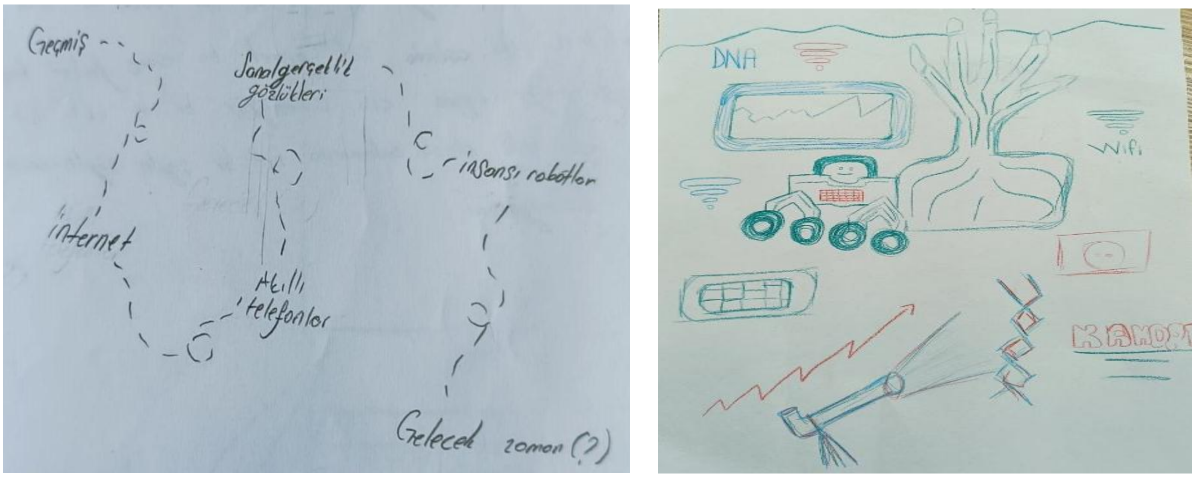

Figure 8. Drawings by S37 and S49

The following are selected student statements related to this theme:

S37: *"I liken artificial intelligence to a journey without boundaries, because no matter how hard you try, it takes everyone on different journeys depending on what you develop or what you want to do. Everyone sheds new light for the future by picking up something on the way with a different route for whatever they want to do with artificial intelligence…"*

S49: *"Artificial intelligence has developed thanks to technology and has also been effective in human life and made life easier. It has been effective in the fields of medicine, education, physics and chemistry, and has shown humanity the light. Many new discoveries and inventions have been introduced thanks to artificial intelligence. New generation robots and new projects have been developed and it has become easier for us to have more information about space and the universe."*

Striking results have emerged within the scope of this theme. For example, S37 likens artificial intelligence to a "journey without boundaries" and draws attention to the role that technology plays in personal and social development. On the other hand, S49 states that artificial intelligence has made great contributions to humanity, especially in fields such as science, education and medicine. According to this student, thanks to artificial intelligence, space exploration, medical innovations and technological projects have accelerated, and humanity has moved towards a brighter future with new discoveries and inventions. These reflections show how students recognize the critical role AI plays in both individual and collective development.

Negative/Positive Aspects of Artificial Intelligence

As a result of examining the students' views, codes were created regarding the positive, neutral and negative aspects of artificial intelligence, and the created codes were brought together under the themes of "Negative/Positive Aspects of Artificial Intelligence". Table 2 provides the themes and codes regarding the positive and negative aspects of artificial intelligence:

Table 2. Participants' Views on the Positive, Neutral, and Negative Aspects of AI

Theme	Category	Sub-Category	Examples from Data	*f*
Positive Perspective	Technological Innovations	New applications	"Cooking robots can help the elderly." (S36)	7
	AI in Daily Life	Integration into daily tasks	"Phones, computers, smart boards make our work easier." (S16)	10
Neutral Perspective	Dual Nature of AI	Advantages and disadvantages	"The good aspect of AI is gaining knowledge; the bad aspect is addiction." (S7)	8
Negative Perspective	Future Risks of AI	Misuse and harm	"If AI falls into the wrong hands, it could mean the end of the world." (S1)	5
	Ethical Concerns	Misuse and bias	"AI could create fake images if misused." (S24)	6
	Human-AI Interaction	Dependency and autonomy	"Independent robots could destroy humanity." (S26)	4

According to the participants' views, three main themes were reached: positive perspective, natural (neutral) perspective and negative perspective. The positive perspective focuses on the aspects of artificial intelligence that make human life easier and provide practical solutions. Participants stated that technological innovations, especially cooking robots, can provide support to elderly individuals and make daily life easier. In addition, it was stated that artificial intelligence-supported tools such as phones, computers and smart boards make significant contributions to many areas of life by speeding up work. This theme expresses that artificial intelligence can be a positive force for society. The natural (neutral) perspective reveals the dual structure of artificial intelligence, which includes both advantages and disadvantages. Participants exhibited a balanced approach, appreciating the benefits of artificial intelligence, such as acquiring knowledge, and acknowledging that this technology can be addictive and that uncontrolled use can have negative consequences. This theme shows how AI is perceived in different contexts and is met with both hope and reservations. Lastly, the negative perspective focuses on potential risks and threats associated with AI. Concerns include its misuse, ethical dilemmas such as fake content creation, and the possibility of autonomous robots posing a danger to humanity. This perspective underscores the consequences of unregulated and unethical AI use.

Discussion

The study revealed that gifted students perceive artificial intelligence (AI) as a human-like entity and evaluate it based on human-machine interactions. The students' descriptions of AI as a robotic brain, a tool that facilitates human tasks, or an entity capable of human-like thinking suggest that they perceive both its cognitive and social capacities. This aligns with the observations of Erten and Goktepeliler (2022), who stated that AI redefines the human-machine relationship, evolving into a system increasingly perceived as human-like. Such perceptions also correspond to the view suggesting that AI is not merely a technical tool but an interactive entity offering functional benefits (Kaplan & Haenlein, 2019). Furthermore, the students' emphasis on AI's potential health risks brings attention to discussions surrounding the physical and mental health implications of technology (Siau & Wang, 2020; Demirkaya & Sarpel, 2018). These findings indicate that students tend to adopt a critical perspective, assessing both the benefits and risks of technology.

The students' positive assessment of AI integration into educational processes and the use of AI-powered tools in classrooms highlights the transformative potential of technology in education. AI offers broad applications in education, particularly in personalizing and enhancing interactivity in learning processes (Holmes et al., 2019; Incemen & Ozturk, 2024). Their emphasis on the role of AI in education is further supported by examples such as teachers using smartboards in classrooms or students engaging in robot design. Graesser et al. (2001) noted that AI strengthens student-teacher relationships and makes education more inclusive. Students' perception of AI as a tool facilitating the comprehension of scientific concepts demonstrates the effectiveness of AI-supported educational tools in boosting learning motivation (Carbonell, 1970). Hence, the aspects of AI that enrich learning experiences may underpin students' positive attitudes toward this technology.

Students associating AI with digital tools reflect its integration into commonly encountered technological devices. By linking AI to computers, smartphones, and televisions, they demonstrate an awareness of the widespread digital integration of technology, particularly among gifted students who are more engaged with and accustomed to digitalization (Kaplan & Haenlein, 2019; Kırık & Ozkocak, 2023). This situation is due to their greater interaction with technology and their familiarity with digitalization. The fact that students see AI as a basic component of social media applications, music platforms and the internet also shows how the effects of this technology on social life are perceived (West & Allen, 2020). In this context, students' awareness of the integration of AI into daily life shows that they have the capacity to evaluate the social effects of technology.

Gifted students' exploration of potential future uses of AI using their imaginations reflects the breadth of their visions regarding technology. Students' development of futuristic and fantastic themes such as robot chefs, systems that assist the elderly, or living in space in relation to AI provides a strong insight into how AI can transform human life in the future. Developing future-oriented and imaginative themes regarding AI provides an important perspective on how AI can shape human life in the future (Bostrom, 2016; Toprak, 2020; Benli & Fırat, 2024). Futuristic perspectives can be considered as an indicator of the desire to explore the evolutionary potential of technology (Aktas, 2024). As emphasized by Siau and Wang (2020), futuristic thoughts regarding the future role of technology support young individuals' critical thinking and creative problem-solving skills. These forward-looking perspectives suggest that AI could shape societal structures and lifestyles in profound ways.

The findings of the study show that students may perceive AI as a threat. Students' fears that AI may get out of control or replace human jobs reflect concerns about the unknown aspects of technology. Russell and Norvig (2016) stated that the rapid development of AI generates anxiety about control and power dynamics over people. Gifted students' apprehensions about AI's ethical and social implications underscore the importance of addressing these aspects in discussions about technology (Toksoy- Cagal & Keskin, 2023; Abanoz & Acar, 2023). The intense interest of male students in the power and control features of AI shows that gender roles in society are reflected in their perceptions of technology (Akyıldız & Akyıldız, 2020). These findings create concerns about the power of AI over people and emphasize the importance of questioning the ethical boundaries of this technology (Kaplan & Haenlein, 2019).

Students emphasizing the relationship between AI and robotics point to its functionality and the conveniences it offers in daily life. Their recognition of robots performing various tasks and the speed AI provides indicates their appreciation for its practical dimensions. Brynjolfsson and McAfee (2014) highlighted how robotic technologies enhance individual efficiency in daily life. The students' anticipation of robots' growing capabilities demonstrates their belief in the increasing integration of AI and robotics into human life, hinting at broader roles these technologies could play in the future.

Gifted students also recognized AI's impact on the gaming industry, highlighting its power in the entertainment sector. Their emotional attachment to game characters and focus on immersive technologies like virtual reality reflect their understanding of the interaction between virtual and real worlds (Russell & Norvig, 2016; Alanoglu & Karabatak, 2020). It is stated that the realistic experiences created by AI in virtual worlds shape how young individuals perceive this technology (Sarıca, 2019; Copgeven et al., 2023). In addition, the fact that students are disconnected from the real-world during games by using virtual reality glasses supports concerns that virtual games carry the risk of weakening social ties. In this context, the effects of AI on social interaction and individual experience in the gaming sector provide insight into the potential consequences of this technology on social structure.

The findings of the study suggest that gifted students evaluate AI as a power that contributes to the development of humanity. The fact that students perceive AI as a technology that sheds light on humanity in fields such as science, education and medicine points to the transformative power of this technology on society. Kaplan and Haenlein (2019) stated that AI plays a key role in accelerating developments in science and technology. The students' view of AI as a boundless field of development reflects their innovative perspective (Öztemel, 2020). Their belief in AI's potential to facilitate new discoveries for humanity emphasizes its role as an indispensable part of the future.

Students' evaluation of both positive and negative aspects of AI reveals their awareness of the dual nature of technology. While students drew attention to its positive aspects such as obtaining information, analyzing accidents, and communication, they also emphasized its negative aspects such as addiction, damaging eye health, and deepfakes. Yılmaz et al. (2021) noted that while AI makes significant contributions to society, it also poses ethical and health-related risks. These findings show that students consider the potential negative aspects of artificial intelligence as much as they appreciate its benefits. Students' sensitivity to the correct use of technology and questioning ethical boundaries provide an important perspective for the responsible development and application of AI. (Dasdemir, et al., 2021; Alanoglu & Karabatak, 2020; Cam, et al., 2021)

Conclusion

This study explored gifted students' perceptions of artificial intelligence (AI) and revealed a variety of perspectives on the societal, educational, and technological roles of AI. The findings suggest that students perceive AI as both a collaborative and competitive entity, with human-machine relationships central to their conceptualizations. This dual perspective highlights the functional benefits of AI, such as problem solving and automation, as well as concerns about ethical implications and risks.

Gifted students emphasized the transformative potential of AI in education, particularly in advancing personalized and interactive learning. They associated AI with tools such as smart boards and robotics, emphasizing its integral role in modern educational practices. However, their critical views on over-reliance on technology, health risks, and ethical dilemmas suggest a nuanced understanding of the impact of AI. The futuristic visions presented by the students exhibited creative and forward-thinking attitudes that envisioned AI's capabilities in innovative areas such as healthcare support, space exploration, and advanced robotics.

This creative approach reflects their capacity to think beyond current technological boundaries and to foresee future societal changes brought about by AI.Students have positive, negative, and naturalistic views of AI. Concerns about AI as a potential threat, including fears of displacement and loss of control, are consistent with broader societal concerns. These perspectives underline the importance of addressing ethical issues in the development of AI and ensuring its responsible integration into human life.

In conclusion, the study suggests a balanced view of the thoughts of gifted individuals, appreciating the promises of AI while critically assessing its risks. These views may inform the development of AI education programs that foster ethical awareness and innovative thinking, preparing students to participate constructively in the evolving presence of AI in society.

Key Implications

Gifted students perceive AI as both a supportive tool and a potential competitor to human capabilities.

The research showed the need for ethical considerations and awareness of the societal impacts of AI.

Their futuristic visions suggest that they are ready to explore the potential applications of AI in a variety of areas.

The study shows that participants may have three types of positive, neutral and negative roles related to AI.

By recognizing and addressing these perspectives, educators and policymakers can foster an environment that balances innovation with ethical responsibility and ensures that AI serves as a tool for collective progress.

Suggestions

Students' association of AI with educational tools indicates that it would be beneficial to implement this technology more broadly in education. In this regard, the integration of AI-supported learning tools, smart boards and interactive robot designs into educational environments should be encouraged.

Considering that gifted students have developed awareness of the possible ethical risks of AI technology, courses addressing the ethical dimensions of AI should be added to educational programs. In these courses, students' awareness of the responsible and ethical use of AI should be fostered and their critical thinking skills should be developed about the potential negative effects of technology.

Considering that students see AI as a futuristic and fantastic technology, competitions and project activities should be organized to support them in researching and developing this potential. Such activities can enable students to develop their creativity and innovative thinking skills.

In line with students' emphasizing the negative effects of digital integration and the risks of AI on health, awareness programs should be organized regarding the health risks associated with long-term use of technology. These programs should be implemented to increase students' digital health awareness and encourage them to use digital tools responsibly.

Educational modules should be developed to provide knowledge and skills in the field of artificial intelligence and robotics at an early age. Workshops and events can be organized to enable gifted students to learn the working principles of robotic systems and AI so that they can interact with these technologies profoundly.

Considering the differences in AI perception observed between male and female students, social and cognitive studies should be conducted to examine the effects of gender on technology perceptions. These studies can be conducted to better understand the effects of gender on technological concepts and to contribute to students developing more balanced perspectives on technology.

Scientific Ethics Declaration

* The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

* The report on the ethical suitability of this research was obtained with the ethics report of Muş Alparslan University dated 03.06.2024 and numbered 8/72.

Conflict Interest Statement

The authors declare that they have no conflict of interest.

Funding

There is no funding in the study.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Compliance of Ethical Standard Statement

Participants attended research processes, with clear instructions and details about the study and data usage provided upfront. Confidentiality of participants' personal information was ensured.

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Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025 https://doi.org/10.55549/jeseh.806

Bibliometric Analysis of Studies on Artificial Intelligence in Environmental and Health Education

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Article Info

Article History

Published:
01 April 2025

Received:
13 January 2025

Accepted:
21 March 2025

Keywords

Artificial intelligence,
Bibliometric analysis,
Environmental education,
Health education

Abstract

While the use of artificial intelligence in education is a prominent area of research, it has also become a collaborative application for educational institutions. These institutions are working to develop AI-based systems to enhance existing educational frameworks. Accordingly, this study conducts a bibliometric analysis of research on artificial intelligence in environmental and health education published between 2020 and 2024 (the past five years), using the Web of Science database. VOSviewer software was employed for the analysis. A search of the Web of Science database using these criteria yielded 640 studies. An examination of the publication distribution by year reveals a notable concentration of publications in 2024. In terms of country-specific contributions, the leading contributors were China, the United States, and England. The most prolific authors in the field were identified as Ai Koyanagi, Brendon Stubbs, and Joseph Firth. In terms of document and citation numbers within journals, the "Journal of Medical Internet Research" emerged as the most prominent. The most frequently cited keywords included "Artificial Intelligence," "Health Education," followed by "Machine Learning," "COVID-19," and "ChatGPT." These findings offer valuable insights into recent advancements in artificial intelligence research within the fields of environmental and health education. This study is anticipated to help researchers identify key trends and offer guidance for future investigations in the field.

Introduction

Global environmental issues such as climate change, biodiversity loss, fossil fuel use, ozone layer depletion, water scarcity, waste management, and environmental pollution make it imperative to increase individuals' environmental awareness and enhance their ecological literacy skills for a sustainable future (Fang&Yang , 2024; Yang & Xiu, 2023). As global environmental problems continue to escalate, comprehensive measures are required to mitigate the effects of climate change and prepare societies for a sustainable future. In light of the economic losses, workforce, and time losses resulting from health issues caused by environmental problems, environmental health services are gaining importance (Remoundou& Koundouri, 2009, Sarmiento et al., 2023). According to the World Health Organization (WHO), environmental health is a discipline that encompasses all aspects of human health, determined not only by physical environmental factors but also by chemical, biological, social, and psychosocial factors (López-Alcarria et al., 2014; Smith, 2013).

Environmental health involves practices aimed at protecting the elements that constitute the environment in ways that safeguard human health, as well as rectifying or reducing harmful conditions that pose a threat to human health. Given the effects of environmental changes on human health, the integration of environmental education and health education to raise environmental awareness should be considered a fundamental necessity for individuals to maintain a healthy life (Boris, 2010). Health education involves the creation of learning opportunities that aim to improve health literacy, enhance knowledge, and develop life skills through communication. Its broad objective is not only to increase awareness of personal health behaviors but also to foster the skills necessary to address the social, economic, and environmental determinants of health and to promote actions for improving health outcomes. This is especially important when examining the content of environmental education, as the two fields significantly overlap and share themes related to individual and community health (Bauman & Karel, 2013; WHO,2013).

Environmental education, aimed at raising awareness about environmental issues, increasing sensitivity, and fostering positive behaviors towards nature, provides individuals and communities with the information needed to understand the causes and consequences of environmental problems (Ozel & Yiğit, 2023). Therefore, the connection between health education and environmental education becomes evident, as both work together to address the broader determinants of health and empower individuals to take action for a healthier environment (Boris, 2010).

Unlike traditional forms of education, environmental education is a holistic and lifelong learning process aimed at raising individuals who investigate and identify environmental problems, participate in problem-solving processes, take effective action to improve the environment, and are aware of their responsibilities (Ural & Dadli, 2020; Samosa et al., 2022; Stelljes& Allen-Gil, 2009). However, conventional environmental education approaches have been criticized for their inability to effectively influence students' attitudes and behaviors toward sustainability. The use of digital technologies, such as artificial intelligence (AI), has the potential to overcome the shortcomings of traditional education systems, leading to a historic transformation (Cao & Jian, 2024; Kamalov et al., 2023; Krstić et al., 2022; Wang et al., 2024).

In recent years, the use of artificial intelligence technologies in education has become increasingly widespread, offering innovative solutions for learning processes. In education, artificial intelligence stands out through various applications, such as providing personalized learning experiences, conducting learning analytics, developing assessment systems, making learning interactive, experiential, and engaging, and offering data-driven feedback to students (Brečka et al., 2022; Holmes et al., 2019). Although the number of studies on the role of artificial intelligence in environmental and health education is steadily increasing, there is a need for a systematic evaluation to determine the general trends, key topics, and research gaps in this field. Bibliometric analysis is a method that provides a comprehensive overview of the literature by using mathematical and statistical techniques to analyze relevant research, examining scientific productivity, citation relationships, collaboration networks, prominent researchers, leading journals, countries, and research trends in a specific academic field (Arias-Chávez et al., 2022Genc & Kocak, 2024; Ulukok- Yıldırım, 2024; Geng et al., 2024; Lopera-Perez et al., 2021).

This study aims to examine academic research on environmental education and artificial intelligence through bibliometric analysis. Publications obtained from the Web of Science international database were analyzed using the VOSviewer program to investigate the distribution of publications over the years, the most productive countries, the most prolific and influential authors, the journals with the highest citation counts, and the distribution of key terms. The findings reveal the current state of AI usage in environmental and health education and highlight trends in literature, providing valuable guidance for future research in the field.

Method

Bibliometric analysis is a quantitative method for examining large-scale scientific literature obtained from various databases, processing the data, and mapping it (Hallinger & Kovacevic, 2019; Kılıcaslan et al., 2025). It also analyzes the general structure and development of scientific works by using various statistical techniques to measure criteria such as the number of articles, collaborations between authors, distribution of publications in journals, and citation counts (Ulukok -Yıldırım, 2024). A well-conducted bibliometric analysis can establish a strong foundation for the innovative and meaningful progression of a research field. It allows researchers to gain a comprehensive overview of the field, identify gaps in knowledge, generate new research ideas, and position their planned contributions effectively within the existing literature (Genc & Kocak, 2024). In this study, bibliometric analysis based on scientific mapping techniques has been used to examine international articles published on the use of artificial intelligence in environmental and health education in journals indexed in the WoS database and to identify the current state of the field.

Purpose and Limitations of the Study

In line with the objectives of the research, it was proposed to conduct a bibliometric analysis that encompasses both a descriptive examination of publications within a specified timeframe and the development of bibliometric maps, adhering to the established guidelines recognized within the scientific community for such studies. This research aims to provide a comprehensive analysis of studies published between 2020 and 2024 in the field of environmental and health education with a focus on artificial intelligence, examining factors such as year, author, citation, journal, country, and keywords, and exploring the relationships among these variables. The study is limited by the decision to use data from the past five years, sourced from the WoS database, the choice of VOSviewer software for bibliometric analysis, and the focus on specific headings for network mapping within the analysis.

Data Collection Process

Bibliometric mapping serves as a spatial representation of the relationships between disciplines, fields, individual publications, or authors. Bibliometric studies enable the identification of trends within a specific domain by quantifying various aspects of research and evaluating the outcomes. Such analyses facilitate the tracking of studies, researchers, institutions, and the scientific progression associated with a given scientific topic (Small, 1999; Martí-Parreño et al., 2016; Kasemodel et al., 2016; Kaban, 2023). So this study employed the bibliometric mapping method to analyze articles on artificial intelligence in environmental and health education across various variables. In this study, the Web of Science (WoS) database was utilized to gather data. Relevant studies were identified through WoS's advanced search query and filtering options. Web of Science (WoS) is a bibliographic database that allows us to download bibliometric data and provides access to various databases (SCI-E, SSCI, A&HCI, etc.) and citation data (Falagas et al., 2008). Figure 1 presents the search codes used in the database. Given that artificial intelligence is rapidly developing, this review focuses solely on research published from 2020 to 2024. On February 18, 2025, a total of 640 studies were retrieved from the WoS database based on the search criteria presented in Figure 1.

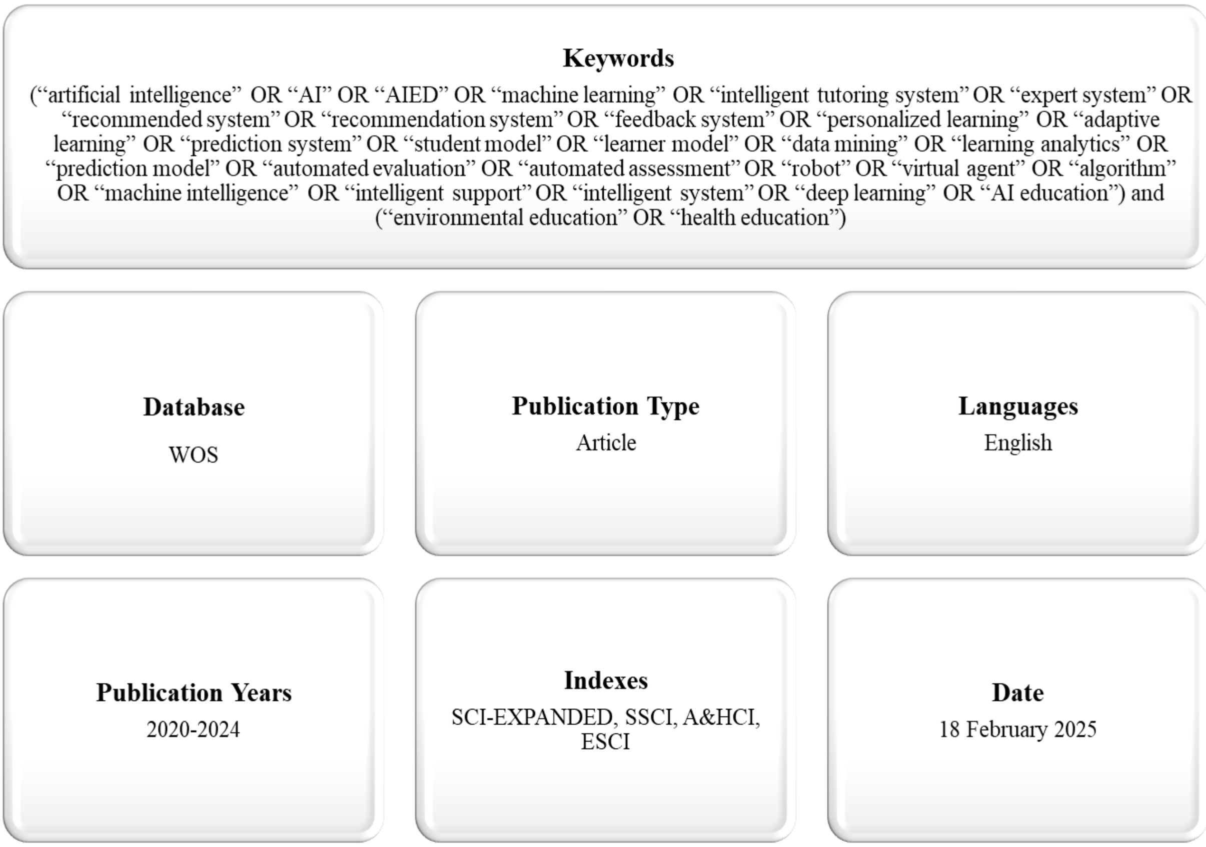

Figure 1. Article Selection Process

Data Analysis

Bibliometric software tools are required to analyze the data obtained from WoS. These tools are used for performance analysis and scientific mapping. VOSviewer is a software tool with excellent visualization capabilities that can perform big data analyses for scientific mapping (Moral-Munoz et al., 2020). VOSviewer supports large databases such as WoS and Scopus. In addition, the VOSviewer program can visualize and present analyses such as co-citation analysis, co-authorship analysis, bibliographic coupling analysis, keyword analysis, and citation analysis using bibliometric mapping methods according to the content of the data. In this study, 640 artificial intelligence-related environmental and health education research articles published in WoS up to February 2025 were analyzed using bibliometric analysis and bibliometric mapping techniques under headings such as year, country, journal, citation, co-citation, and keywords. The data downloaded from WoS were visualized using the bibliometric software tool VOSviewer (version 1.6.20), providing a descriptive and quantitative presentation of the current state. Prior to each analysis, the relevant data were thoroughly examined, and necessary data cleaning procedures were carried out, such as correcting author, journal, and institution names written in different languages and characters or creating 'thesaurus files' for identical or similar words.

Findings

Figure 2 displays the distribution of articles retrieved from the WoS database, highlighting the number of publications from 2020 to 2024. The data reveals noticeable variations in the volume of scholarly work across this period. This temporal analysis offers valuable insights into the evolving trends and dynamics of research activity over the specified years.

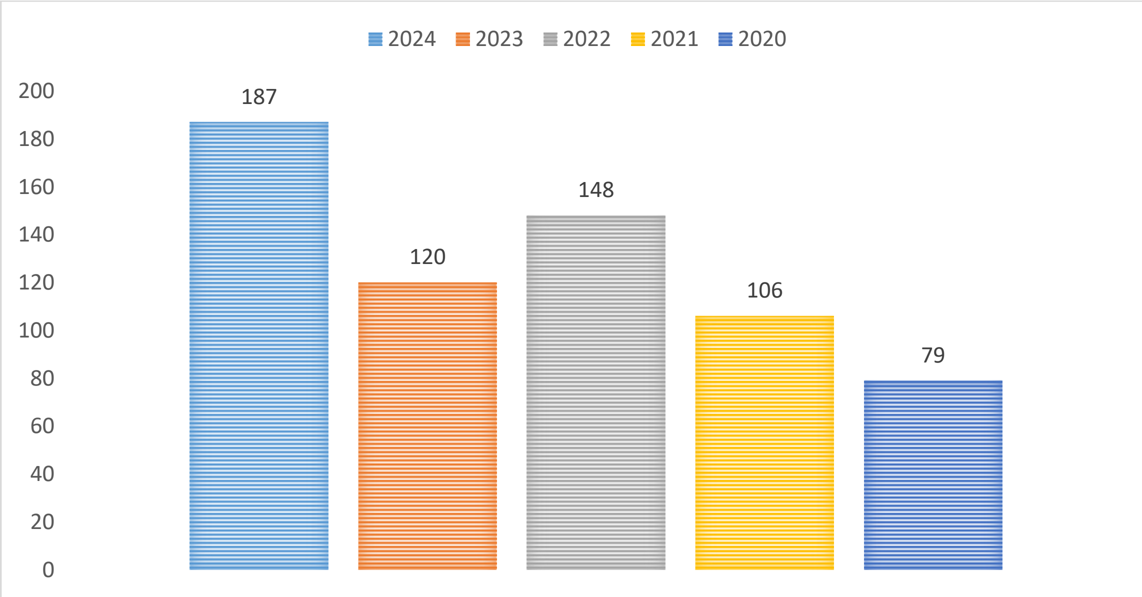

Figure 2. Distribution of publications by year

As shown in Figure 2, while research on AI in environmental and health education has increased between 2020 and 2022, there was a decline in 2023. However, it is seen that studies in this field increased again in 2024 and the number of publications reached its peak.

Table 1 and Figure 3 present the geographical distribution of publications. To identify the most productive countries in scientific research, a threshold was set, requiring at least 10 publications and a minimum of one citation. This criterion ensures the inclusion of countries with a substantial impact on scholarly output, providing a more comprehensive understanding of global research dynamics.

Table 1. Top ten contributed countries

Rank	Country/Region	Number of publications	Citation	TLS
1	China	232	1064	4
2	USA	124	1252	16
3	England	72	1041	18
4	Australia	38	477	0
5	Spain	30	493	12
6	Taiwan	28	154	10
7	India	22	278	0
8	France	21	345	12
9	Canada	21	308	1
10	Saudi Arabia	16	187	0

An analysis was performed using 23 observation units, revealing relationships between them. Seven clusters, 31 links, and a total link strength of 51 were identified. The countries with the highest number of citations are the USA (1,252 citations), China (1,064 citations), and the UK (1,041 citations). In terms of publication volume, the ranking is as follows: China (232 publications), the USA (124 publications), and the UK (72 publications).

A citation network map was created based on the criteria of a minimum of three publications and at least one citation to identify citation networks among authors. The resulting table and map are presented in Table 2 and Figure 4.

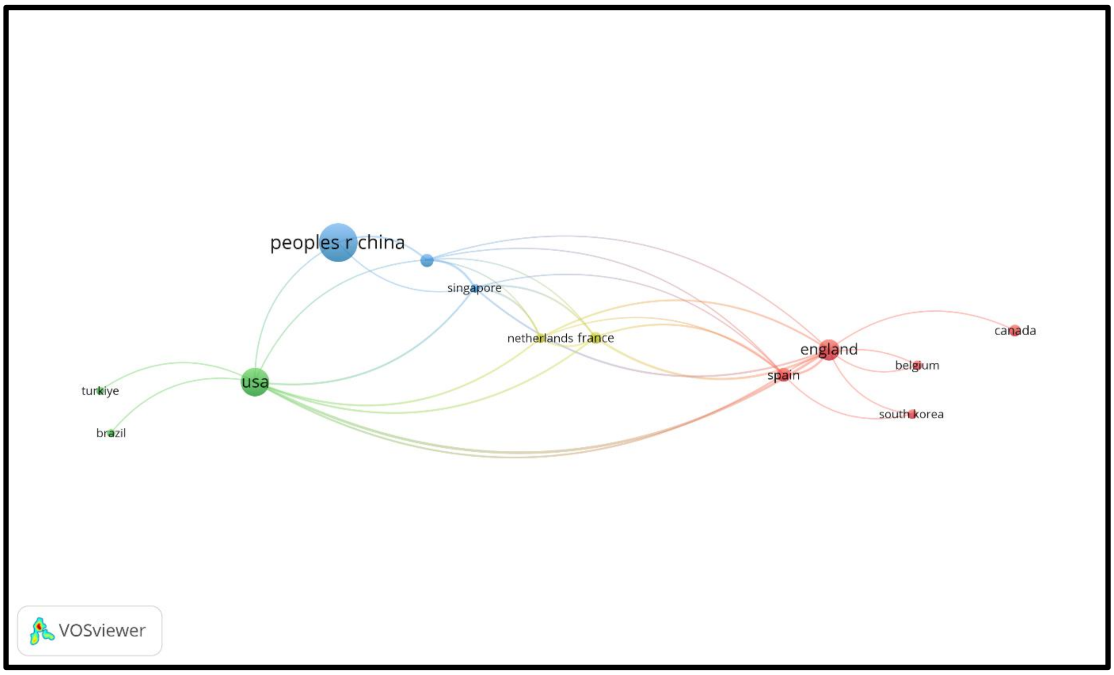

Figure 3. Network diagram of countries

Table 2. Top ten contributed researchers

Rank	Author	Number of publications	Citation	TLS
1	A. Koyanagi	13	308	8
2	B. Stubbs	12	308	8
3	J. Firth	8	252	0
4	J. I. Shin	4	181	4
5	F. Hu	6	123	0
6	J. Y. Bernard.	5	114	20
7	D. Vancampfort	9	110	4
8	Lee Smith	5	92	4
9	R. Shi	5	90	0
10	B. Heude	5	83	20

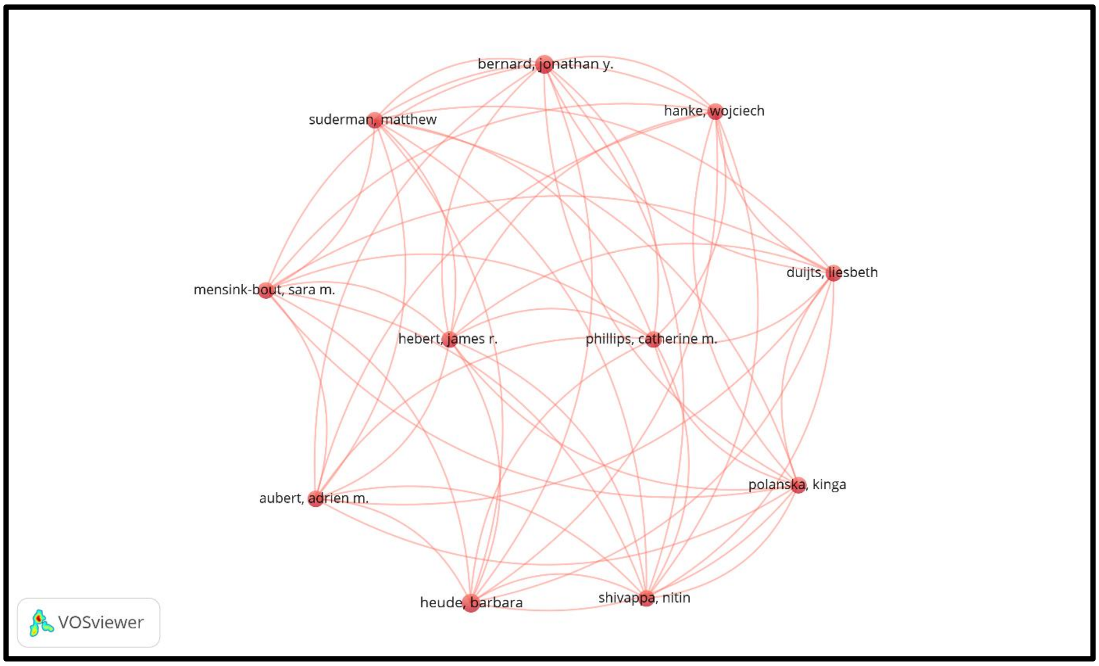

Figure 4. Author citation network

In an analysis conducted on 29 interconnected units, one cluster, 55 link, and total link strength of 110 were identified. The most cited authors are Ai Koyanagi and Brendon Stubbs with 308 citations and Joseph Firth with 252 citations. Additionally, 'co-citation' was chosen as the analysis type, with 'cited authors' designated as the analysis unit within the VOSviewer software (Table 3). A threshold value of 24 was applied to reduce clutter in the data visualization. The resulting map is presented in Figure 5.

Table 3. Ranking of the most influential researchers by co-citation

Rank	Author	Co-Citation	TLS
1	WHO	104	86
2	B. Stubbs	26	146
3	D. Vancampfort	25	152
4	J. Zhang	19	31
5	A. Bandura	18	2
6	X. B. Qu	17	38
7	Y. Yang	17	26
8	OpenAI	17	20
9	Y. Liu	17	13
10	J. Y. Ma	16	16

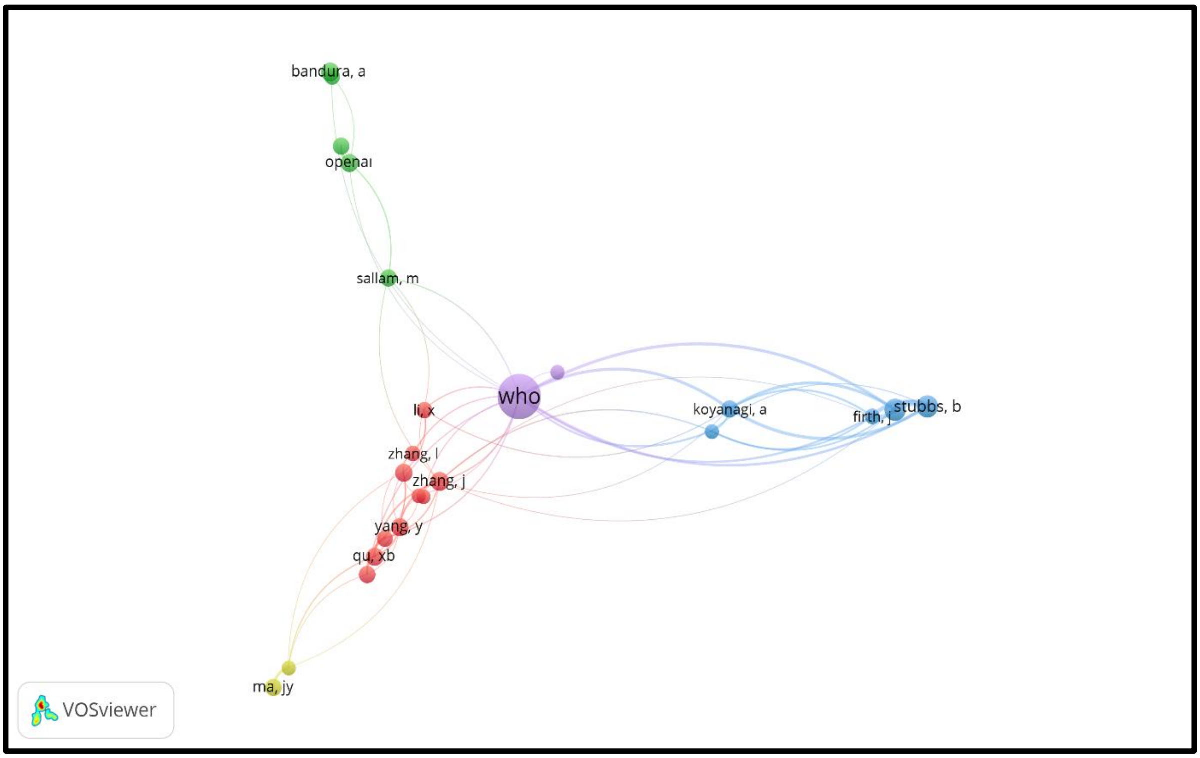

Figure 5. Co-author citation network

When the map in Figure 5 is examined, it is seen that there are five different colored clusters related to the common referenced authors. WHO is in the center of the names in the purple cluster, at the center of the red cluster is J. Zhang, at the center of the blue cluster is B. Stubbs, at the center of the yellow cluster is J. Y. Ma and at the center of the green cluster is OpenAI. G-J.

Journals with a minimum of five publications were included in the analysis. A citation analysis was performed to identify the most influential publications in the field. The results revealed that 22 out of 392 journals published ten or more studies on the topic. Table 4 presents the top ten most influential journals.

According to the findings in Table 4, the journals "Journal of Medical Internet Research" journal is in first place with 10 articles and 177 citations. "JMIR Medical Education" ranks second with 7 publications and 86 citations. It is followed by the "International Journal of Environmental Research and Public Health" with 12 articles and 78 citations. As can be seen from the Table 4, the TLS values of the journals are zero, so there is no connection between the journals.

Table 4. The most influential journals

Rank	Journals	Number of publications	Citation	TLS
1	Journal of Medical Internet Research	10	177	0
2	JMIR Medical Education	7	86	0
3	International Journal of Environmental Research and Public Health	12	78	0
4	Frontiers In Psychology	15	73	0
5	BMC Public Health	10	68	0
6	JMIR Formative Research	10	66	0
7	Applied Sciences-Basel	5	59	0
8	Health Education & Behavior	5	48	0
9	Sustainability	6	40	0
10	Scientific Reports	8	34	0

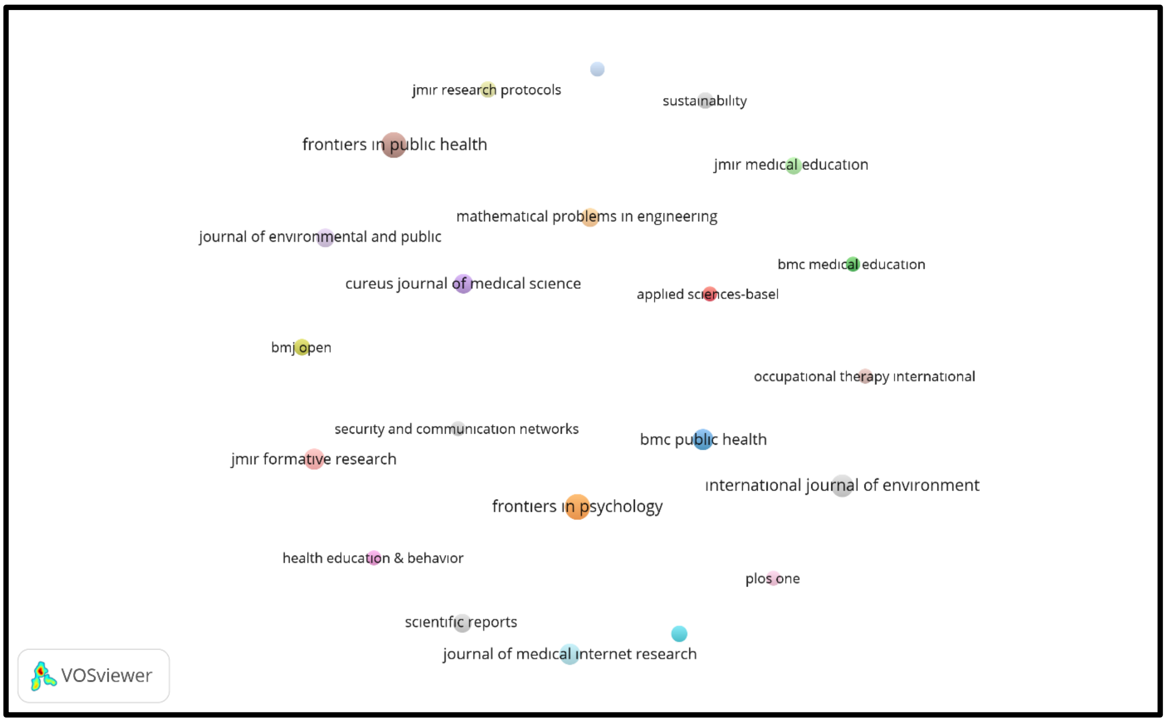

Figure 6. Journal network

A total of 2170 keywords were used across 640 publications related to AI in environmental and health education. The minimum threshold for keyword frequency in VOSviewer was set to 7. As a result of the analysis, 23 keywords, 5 clusters, 89 links, and a total link strength of 207 met the usage criteria. Table 5 presents the top ten most influential keywords.

Table 5. The most influential keywords

Rank	Keyword	Occurrences	TLS
1	Artificial Intelligence	85	84
2	Health Education	65	60
3	Machine Learning	33	26
4	Covıd-19	25	22
5	ChatGPT	19	35
6	Mental Health	17	13
7	Deep Learning	16	10
8	Education	15	22
9	Health Literacy	14	9
10	Digital Health	13	20

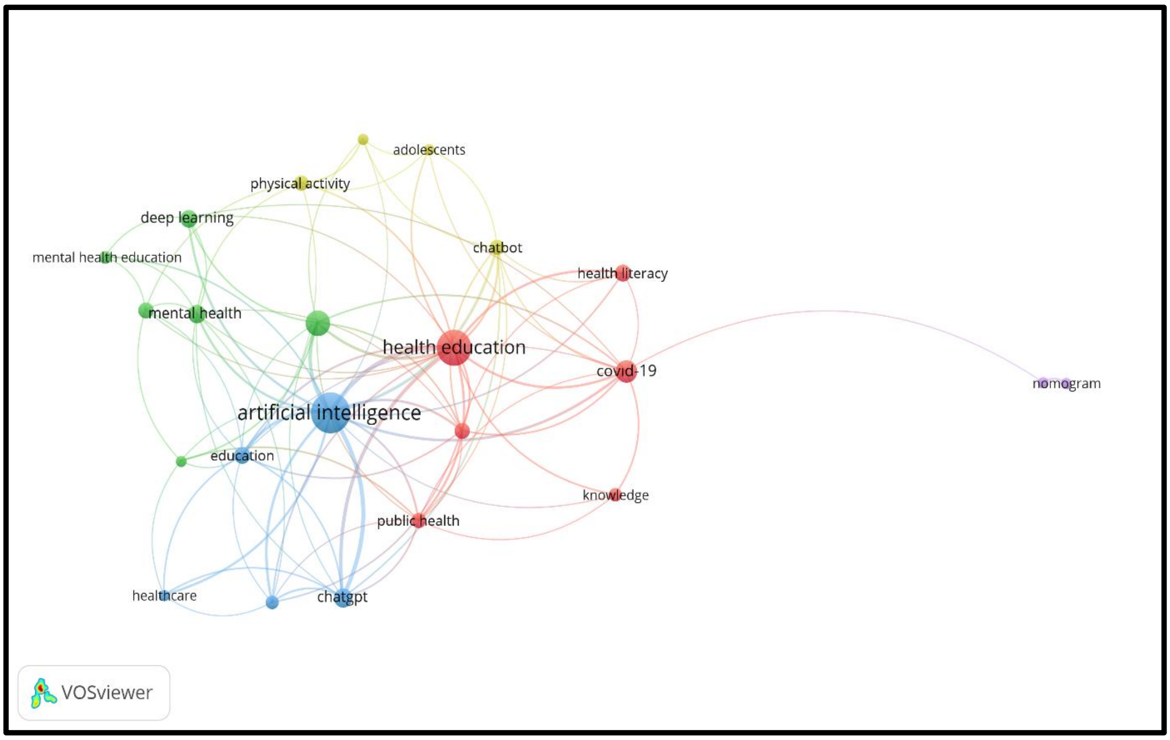

Figure 7. Keywords network

As shown in Figure 7, the first red cluster contains the words covıd-19, digital health, health education, health literacy, knowledge and public health. The second cluster, colored green, includes data mining, deep learning, machine learning, mental health, mental health education and social media. The words artificial intelligence, ChatGPT, education, healthcare and medical education are included in the blue cluster. The fourth cluster is yellow. The prominent keywords in this cluster are adolescents, chatbot, depression and physical activity. The last cluster is purple and contains nomogram and prediction model keywords. Artificial intelligence, health education, machine learning are the most frequently used keywords.

Conclusion and Discussion

The publications related to AI in environmental and health education were retrieved from the Web of Science (WoS) and analyzed in an objective and comprehensive manner. This study includes articles published in English, and it covers a total of 640 articles indexed in the WoS database on the topic of AI in environmental and health education from 2020 to 2024 (the past five years), which were subjected to bibliometric analysis.

The use of AI in environmental and health education has demonstrated steady growth over the past five years. From 2020 to February 2025, there was a significant increase in the number of related publications. In 2020, 79 publications were recorded, which rose to 106 in 2021, further increased to 148 in 2022, and then slightly declined to 120 in 2023. By 2024, the number of focused publications had reached 187. Despite this growth, the overall volume of publications remains limited, and the distribution of research outputs across different countries remains uneven. This disparity may be attributed to variations in resource allocation, technological development levels, and the availability of specialized training (Nahar, 2024).

China has been a leading contributor to the production of articles on artificial intelligence and has also ranked first in citation numbers, indicating the global influence and impact of its research. However, despite China ranking first in terms of article production, the United States surpassed China in citations. This suggests that although the United States produced fewer articles, its research may have had a more significant impact. While Taiwan surpasses countries such as India, France, Canada and Saudi Arabia in the number of articles, it is at the bottom in the number of citations.

Upon examining the distribution of journals with the highest number of publications on the subject, it was found that prominent journals related to the use of AI in education emerged as key contributors. The most published journals were Frontiers In Psychology and International Journal of Environmental Research and Public Health.

When the number of citations per article was examined, the journals Journal of Medical Internet Research, JMIR Medical Education and International Journal of Environmental Research and Public Health were found to be the most popular ones. When examining the authors of articles published on the use of artificial intelligence in environmental and health education, the number of citations and the number of publications were used to determine how much they contributed to the field. Individually, A. Koyanagi is the most cited author and has written the most articles.

Regarding the keywords defined by the authors, 'artificial intelligence' and 'health education' appeared at the top of the list, reflecting the central focus of the study. However, it was notable that terms such as 'ChatGPT' were present, indicating the influence of emerging technologies targeting end-users, and 'COVID-19,' suggesting research on the interaction between the pandemic and AI-mediated education. Additionally, terms like 'machine learning' and 'deep learning' highlighted the specific techniques and tools that have been extensively explored within this educational context. These key terms provide a comprehensive overview of the dominant themes and areas of interest concerning the relationship between AI and education. Mental health, health literacy and digital health keywords are also among the most frequently used keywords in health education studies.

From a theoretical perspective, this work not only addresses a gap in specialized literature but also lays a robust foundation for future research. The intersection of environmental education and health education presents both opportunities and challenges. An interdisciplinary approach, coupled with global collaboration, will be crucial to navigating this complex and evolving research domain. From a practical standpoint, there are several key managerial implications for educational institutions and leaders. Educational administrators should assess and adapt curricula to incorporate competency-based elements, reflecting the rapid advancements of artificial intelligence in education. Furthermore, it is essential for administrators to ensure that educators and staff are adequately equipped to integrate these technologies and stay abreast of technological advancements in the field.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

Funding Declaration

The authors did not receive support from any organization for the submitted work.

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JESEH
Journal of Education in Science, Environment and Health
Volume 11, Issue 2, 2025
https://doi.org/10.55549/jeseh.813

The Heart and Art of Robotics: From AI to Artificial Emotional Intelligence in STEM Education

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Article Info

Article History

Published:
01 April 2025

Received:
13 October 2024

Accepted:
17 March 2025

Keywords

Artificial intelligence,
Artificial emotional intelligence,
Robotics,
STEM,
STEAM

Abstract

The evolution of artificial intelligence (AI) and robotics in education has transitioned from automation toward emotionally responsive learning systems through artificial emotional intelligence (AEI). While AI-driven robotics has enhanced instructional automation, AEI introduces an affective dimension by recognizing and responding to human emotions. This study examines the role of AEI-powered robotics in fostering student engagement, cognitive development, and social-emotional learning (SEL) across early childhood, K-12, and higher education. Constructivist and experiential learning theories provide a foundation for integrating emotionally intelligent robotics into interdisciplinary and transdisciplinary STEAM education. Findings indicate that AEI enhances motivation, problem-solving, and collaboration by creating adaptive learning environments that respond to student affective states. However, challenges such as data privacy, inaccuracies in emotion recognition, and access to robotics must be addressed to ensure ethical implementation. The study advocates for further interdisciplinary research, professional growth, and infrastructure investment to optimize AEI-powered robotics in education. The study also emphasizes prioritizing emotionally intelligent interactions for AEI-driven robotics that represents a shift toward human-centered, AI applications for supporting personalized learning and holistic student development. Future directions include refining affective computing models and fostering ethical AI and AEI frameworks to ensure responsible and effective implementation in early childhood through higher educational settings.

Introduction

The rapid evolution of artificial intelligence (AI) and robotics has introduced new possibilities for education and learning design. While AI-powered tools provide automated support for instruction and assessment, artificial emotional intelligence (AEI) has emerged as a promising development that integrates affective and social dimensions into intelligent learning systems (Salas-Pilco, 2020). Robotics, particularly in educational settings, is increasingly utilized to foster cognitive, social-emotional, and problem-solving skills (Uslu et al., 2023). As robotics in education progresses from pre-programmed automation toward adaptive and emotionally responsive interactions, educators must critically evaluate its role in supporting student engagement, motivation, and personalized learning experiences.

Educational robotics has been widely studied as a tool that enhances STEM (science, technology, engineering, and mathematics) learning and fosters collaborative, inquiry-based approaches (Miglino et al., 2021). Constructivist perspectives emphasize that students benefit from hands-on learning with robotics, allowing them to experiment with programming, engineering, and problem-solving in real-world contexts (Zhu & Atompag, 2023). Additionally, robotics is not only confined to cognitive development but has also shown promise in supporting social-emotional learning (SEL) by enabling interactions that encourage communication, teamwork, and emotional regulation (Salas-Pilco, 2020; Uslu et al., 2023). However, while AI-driven robotics enhances computational thinking and self-efficacy, AEI-based robotics introduces an additional layer of engagement. Artificial emotional intelligence in robots provides AI that recognizes, interprets, and responds to human emotions, potentially reshaping educational experiences.

The shift from AI to AEI in education presents both opportunities and challenges. AI-driven robotics has been effective in automation, adaptive learning, and tutoring systems, yet it often lacks the affective and social elements that are integral to human learning (Salas-Pilco, 2020). Artificial emotional intelligence, by contrast, seeks to bridge this gap by developing emotionally intelligent robotic interactions that respond to students' needs in a more human-like manner.

In this study, the authors posit the potential for AEI-powered robotics to foster greater motivation, deeper learning engagement, and more personalized educational interactions (Salas-Pilco, 2020; Uslu et al., 2023). While AI-driven systems have demonstrated effectiveness in automating instructional processes and adapting to students' cognitive needs, the shift toward AEI introduces the possibility of emotionally attuned learning experiences that extend beyond mere content delivery. Artificial Emotional Intelligence-powered robotics possesses the potential to enhance student-teacher interactions by recognizing emotional cues, adjusting responses accordingly, and promoting a more responsive, human-like engagement with learners.

As educational institutions consider integrating AI and AEI-driven robotics into classrooms, it is essential to explore their pedagogical implications, including their capacity to support constructivism, inquiry-driven, and socially interactive learning environments (Atompag & Zhu, 2023). To address these considerations, this study examines the evolving role of AEI in education, highlighting its impact on student motivation, collaboration, and individualized learning pathways. The authors' study synthesizes current research and discusses potential applications to provide a foundational framework for integrating AEI in future educational settings while identifying emerging challenges and opportunities for educators and policymakers.

Theoretical Background

History of Artificial Intelligence in Robotics

The development of AI can be traced back to the mid-20th century when Alan Turing introduced the concept of machines that could simulate human thought (Cebollada et al., 2021). Early AI models were centered on rule-based systems, which relied on predefined logical structures to process information. However, as computational power advanced, AI evolved into machine learning (ML), where algorithms could learn from data and improve performance over time. In this context, algorithms refer to a set of mathematical rules and computational procedures that enable machines to analyze patterns, make predictions, and adjust their output based on new data.

A subset of ML, known as deep learning (DL), further enhanced AI's capabilities by utilizing artificial neural networks to recognize patterns, classify data, and performing complex tasks such as image recognition, natural language processing, and autonomous decision-making (Soori et al., 2023). Neural network advancements have significantly influenced robotics, allowing machines to adapt to changing environments, learn from experience, and perform tasks once thought to require human intelligence (Ren et al., 2023).

Machine Learning and DL are central in robotics, particularly in autonomous navigation, object detection, and human-robot collaboration. Machine learning enables robots to refine their responses based on past interactions, while DL enhances their ability to process large volumes of visual and sensor data (Cebollada et al., 2021). These technologies have revolutionized robotic perception and decision-making, enabling robots to navigate complex environments, recognize objects accurately, and adapt to unforeseen circumstances. Their applications extend across multiple domains, from robot-assisted surgeries that require precision and adaptability to industrial automation, where predictive analytics optimize production efficiency. AI-driven robotics supports personalized learning experiences in education by tailoring instructional content to students' needs and fostering engagement through interactive and adaptive systems (Zeng et al., 2020).

The Path toward Cognitive Intelligence

Artificial Intelligence-driven robotics has led to the emergence of cognitive intelligence, allowing machines to interpret human emotions, adjust their interactions accordingly, and assist in decision-making (Ren et al., 2023). Unlike traditional AI, which focuses primarily on computational efficiency and automation, cognitive intelligence seeks to bridge the gap between technical precision and human-like responsiveness. The ability to recognize and respond to emotional cues enhances the potential for robots to serve as companions in healthcare, tutors in classrooms, and collaborators in workspaces, offering a more intuitive and human-centered approach to AI implementation. The increasing sophistication of AI-powered robotics raises important considerations for educators and policymakers, as integrating these systems into learning environments requires a balance between automation and human interaction (Soori et al., 2023). Ensuring that AI remains an enhancement rather than a replacement for human educators will be critical in fostering effective and ethical applications in future classrooms.

As AI technology advances, researchers focus on AEI with an aim to equip robots with social and emotional awareness to enhance collaborative learning and student engagement. Unlike traditional AI, which prioritizes efficiency and task execution, AEI seeks to create more human-like interactions by recognizing and responding to students' affective states (Cebollada et al., 2021). The shift from AI to AEI represents a fundamental transformation in how AI-driven robotics is applied in education, moving from purely algorithmic approaches to emotionally responsive and adaptive learning systems (Figure 1). Understanding the historical trajectory of AI, from its early computational roots to machine learning, deep learning, and now AEI, provides a foundation for exploring its pedagogical implications and the future of emotionally intelligent robotics in education (Ren et al., 2023; Soori et al., 2023).

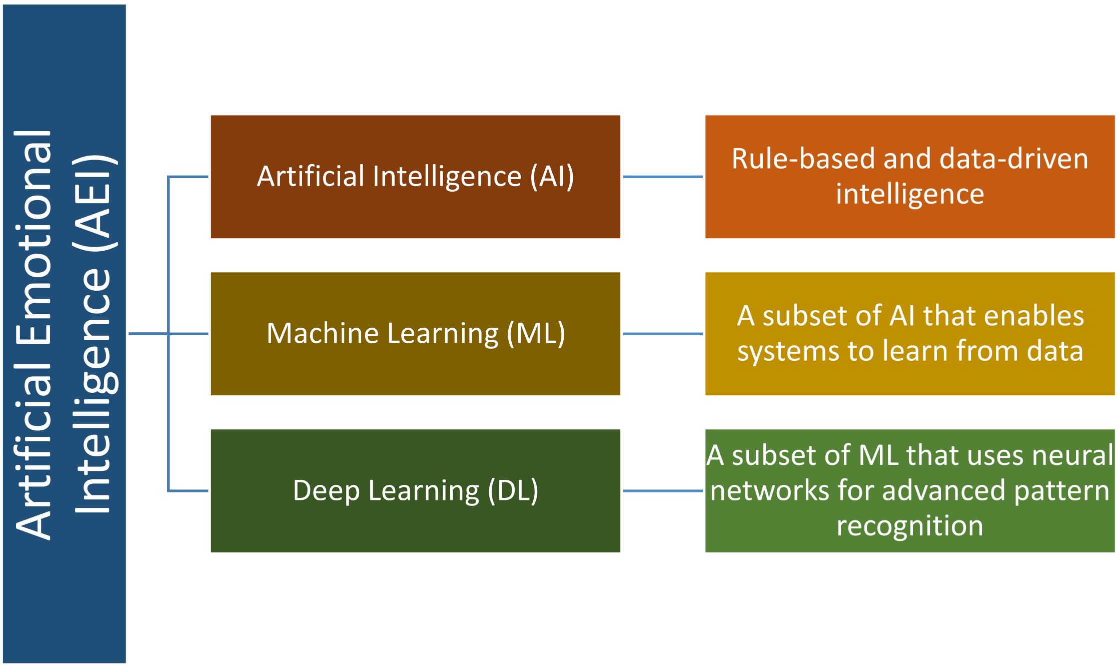

Figure 1. Emotion recognition, interpretation, and responsive interaction of AEI

History of Robotics Automation to Intelligence

The origins of robotics can be traced back to the early Industrial Revolutions, which fundamentally transformed manufacturing and technological progress. The First Industrial Revolution (IR 1.0) introduced mechanical systems driven by steam power, establishing the foundation for automation in industry (Groumpos, 2021). The Second Industrial Revolution (IR 2.0) saw the rise of electrical power, leading to the development of assembly lines and electrically operated machinery, increasing efficiency and precision.

The Third Industrial Revolution (IR 3.0), often referred to as the Digital Revolution, introduced computers and microprocessors, enabling automated production systems and early forms of AI-driven robotics (Elayyan, 2021; Ribeiro et al., 2021). The Fourth Industrial Revolution (IR 4.0), also known as Industry 4.0, expanded robotics through AI, ML, DL, and the Internet of Things (IoT), creating autonomous systems capable of learning, adapting, and interacting with their environment (Jafari et al., 2022; Mhlanga, 2022; Rotatori et al., 2021).

More recently, the Fifth Industrial Revolution (IR 5.0) has emerged as a human-centric evolution of Industry 4.0, emphasizing collaboration between humans and intelligent systems (Jafari et al., 2022; Noble et al., 2022). Unlike IR 4.0, which focuses on smart automation, IR 5.0 highlights AI and robotics designed for sustainability, resilience, and ethical decision-making in various fields, including education. The shift from Industry 4.0 to Industry 5.0 represents a transition toward emotionally intelligent robotics, ensuring AI systems enhance human capabilities rather than replace them (Tinmaz, 2020).

Robotic Interactions for a Human Touch

The evolution of robotics has led to significant advancements in cognitive robotics. Unlike traditional automation, which relies on pre-programmed commands, cognitive robots can perceive, reason, and make autonomous decisions (Levesque & Lakemeyer, 2010). The transition, facilitated by AI and neural networks, has expanded robotics beyond industrial applications, integrating them into healthcare, education, and service industries (Matthews et al., 2021).

A key development in robotics has been the rise of humanoid robots, which prioritize social interaction alongside mechanical efficiency. Early humanoid systems, such as ASIMO by Honda, focused on bipedal movement and dexterity, while modern AI-powered robots integrate speech recognition, facial expressions, and contextual decision-making (Kajita et al., 2014). Advancements in robotics, particularly through AEI, are paving the way for emotion-responsive systems that can engage with humans in more natural and adaptive ways.

However, the increasing presence of AI-driven robotics also raises philosophical and ethical concerns, particularly regarding job displacement, data privacy, and ethical decision-making in autonomous systems (Ribeiro et al., 2021). As AEI-driven robotics becomes more prevalent in education and social domains, researchers must ensure that these systems support human learning and development rather than replace human agency. A deeper historical understanding of robotics, from mechanical automation to cognitive and emotionally intelligent systems, is essential for addressing AEI's role in education and beyond (Table 1).

Table 1. Industrial revolutions and robotics pathway to AEI

Industrial Revolution	**Key Technologies**	**Impact on Robotics**	**Pathway to AI & AEI**
First IR (1760-1840)	Steam engines, mechanization	Early mechanical automation	No AI; focus on machinery replacing manual labor
Second IR (1870-1914)	Electrical power, mass production	Introduction of electromechanical systems	Automation advances but no AI integration
Third IR (1950s-Present)	Computers, microprocessors, digital systems	Robotics emerge for industrial automation	Basic AI (rule-based), early ML applications
Fourth IR (2011-Present)	AI, ML, DL, IoT, Cognitive Robotics	Adaptive robots, autonomous systems	AEI-driven humanoid robots, emotion-responsive AI
Fifth IR (Emerging)	Human-centric AI, AI ethics, sustainable automation	Human-machine collaboration, socially responsible robotics	Emotion-aware AI, AI-driven ethics, sustainable tech

Artificial Emotional Intelligence

Enhancing Human-Machine Interaction

Artificial Emotional Intelligence represents a significant advancement in the field of AI by incorporating the ability to recognize, interpret, and respond to human emotions. Unlike traditional AI, which primarily focuses on logic-driven decision-making, AEI seeks to simulate emotional intelligence by analyzing facial expressions, speech patterns, physiological responses, and contextual cues (Kumar & Martin, 2023). Emotional recognition is facilitated through a combination of ML and DL models, which process data from various sources to detect emotional states with increasing accuracy. Facial emotion recognition, for example, leverages computer vision and neural networks to classify emotions such as happiness, anger, sadness, and surprise (Narimisaei et al., 2024). The integration of speech emotion detection and multimodal data fusion enhances human-machine interactions, making technology more intuitive and responsive in education, healthcare, and service industries.

The development of AEI has the potential to bridge the gap between human cognition and AI, fostering more natural, engaging, and empathetic interactions. Emotion recognition technologies are already being implemented in customer service automation, mental health monitoring, and personalized learning platforms (Kambur, 2021). Within educational settings, AEI plays a transformative role by adapting instructional delivery based on students' affective states, thereby improving engagement, motivation, and learning outcomes. Artificial intelligence-powered tutors equipped with AEI can detect frustration, confusion, or boredom and adjust lesson pacing accordingly (Kumar & Martin, 2023). However, implementation raises ethical considerations concerning privacy, data security, and biases in emotion detection algorithms (Narimisaei et al., 2024). Interdisciplinary collaboration is essential to develop transparent, bias-aware, and ethically guided AI systems that prioritize human well-being in their deployment.

Researchers continue to explore ways to enhance context-aware emotion recognition by integrating cultural, linguistic, and individual variations in emotional expression. Advancements in AEI models seek to move beyond surface-level emotion detection, incorporating behavioral patterns, sentiment analysis, and adaptive response mechanisms to create more meaningful human-machine interactions (Kambur, 2021; Narimisaei et al., 2024). Intelligent learning environments designed with AEI-driven systems could provide emotional support, personalized feedback, and dynamic engagement strategies tailored to individual students. A deeper understanding of AEI's evolution and potential allows for a more informed approach to its integration in future educational settings, ensuring that robots and AI systems are facilitators of human growth rather than mere computational tools.

Enhancing Human-Machine Synergy

The integration of AEI in robotics represents a transformative shift in human-robot interactions, expanding beyond task-based automation to socially intelligent engagement. Traditional robotics primarily focused on mechanization and efficiency, with early applications emphasizing automation in industrial and computational domains. However, as robotic applications extend into healthcare, education, and service industries, the necessity for robots to interpret and respond to human emotions has become increasingly evident (Bengani, 2023). Unlike conventional AI, AEI-driven robotics incorporates affective computing, natural language processing (NLP), and multimodal emotion recognition, enabling machines to perceive, interpret, and react to human emotions dynamically (Hudson, 2023). The advancements in cognitive robotics further allow for adaptive, context-aware responses, making interactions with AI-powered systems more intuitive and human-like (Lynch, 2021).

Developing emotionally intelligent robots requires a framework that integrates sensing, computing, and acting based on affective cues. Emotion recognition technology enables robots to capture facial expressions, voice modulation, and physiological signals, facilitating real-time emotional appraisal and response modulation (Marcos-Pablos & García-Peñalvo, 2022). Robots equipped with deep learning and reinforcement learning models refine their ability to adapt interactions based on previous human-robot exchanges, enhancing their social acceptability and functional effectiveness (Seyitoğlu & Ivanov, 2024). The emotional intelligence embedded in these systems improves user satisfaction and fosters trust and engagement, particularly in domains such as elder care, therapeutic interventions, and education. In an educational setting, AEI-driven tutors can recognize student frustration or boredom and adjust instructional methods accordingly, creating personalized learning experiences that support cognitive and emotional development (Bengani, 2023; Kumar & Martin, 2023).

Despite its promise, implementing AEI in robotics presents several technical, ethical, and philosophical challenges. Ensuring privacy, data security, and the ethical use of emotion recognition data remains a significant concern, particularly in AI-driven surveillance and algorithmic governance (Lynch, 2021). Additionally, limitations in current emotion detection algorithms, such as cultural and individual variations in emotional expression, necessitate ongoing refinement in contextual awareness (Marcos-Pablos & García-Peñalvo, 2022). As the field evolves, research must emphasize transparency and accountability in designing emotionally intelligent AI systems that enhance human-AI collaboration rather than replace human agency. Artificial Emotional Intelligence possesses the potential to revolutionize human-machine interactions, making technology more empathetic, responsive, and adaptable to diverse social contexts (Hudson, 2023).

Enhancing Human-Machine Learning

The incorporation of AEI in educational settings has the potential to revolutionize learning experiences by creating emotionally responsive and adaptive learning environments. Artificial Emotional Intelligence extends beyond traditional artificial intelligence by analyzing, interpreting, and responding to students' emotional states, fostering engagement, motivation, and personalized learning (Fernández Herrero et al., 2023). Unlike conventional AI-driven educational tools, AEI-powered systems utilize emotion recognition software, natural language processing (NLP), and multimodal affective computing to assess student emotions in real-time and adjust instructional approaches accordingly (Melweth et al., 2023; Marcos-Pablos & García-Peñalvo, 2022). Artificial Emotional Intelligence advancement aligns with research indicating that emotional intelligence is a crucial factor in academic success, as it influences students' ability to regulate emotions, engage with learning materials, and persist through challenges (Dignam & Taylor, 2024; Marcos-Pablos & García-Peñalvo, 2022).

Integrating AEI-powered learning technologies into classrooms enables adaptive feedback mechanisms that support both cognitive and emotional learning processes. Artificial Intelligence tutors equipped with affective computing capabilities can detect frustration, confusion, or disengagement and modify instructional strategies in real time, offering encouragement, hints, or alternative explanations to maintain student motivation (Erol et al., 2020; Kumar & Martin, 2023). Furthermore, emotion recognition systems facilitate teacher interventions, allowing educators to monitor student engagement and emotional responses during lessons (Hudson, 2023). Research suggests that students prefer interactive, participatory learning experiences, and AEI-powered tools can promote student-centered, emotionally attuned learning environments (Fernández Herrero et al., 2023).

Despite these benefits, implementing AEI in education presents challenges, particularly regarding data privacy, bias in emotion detection algorithms, and the ethical implications of emotional surveillance (Melweth et al., 2023). Ensuring that AEI-driven systems respect student privacy and provide accurate emotional assessments remains a priority for policymakers and educational technology developers. Additionally, ongoing refinements in DL models are needed to enhance the accuracy of emotion recognition across diverse cultural and individual differences (Marcos-Pablos & García-Peñalvo, 2022). Moving forward, collaborative efforts between educators, psychologists, and AI researchers will be essential to developing ethical, effective, and comprehensive AEI-driven educational tools that empower students both academically and emotionally (Dignam, 2025).

Figure 2 illustrates how Neural Networks, NLP, and Emotion Recognition interact within AEI systems to create adaptive, emotionally responsive learning environments. Each component possesses a distinct role in processing and interpreting human emotions: neural networks identify patterns in speech and facial expressions, NLP analyzes language and tone, and emotion recognition integrates multiple cues to assess affective states. The AEI system synthesizes these inputs, adjusting instructional strategies in real-time to enhance both cognitive and emotional engagement in educational settings.

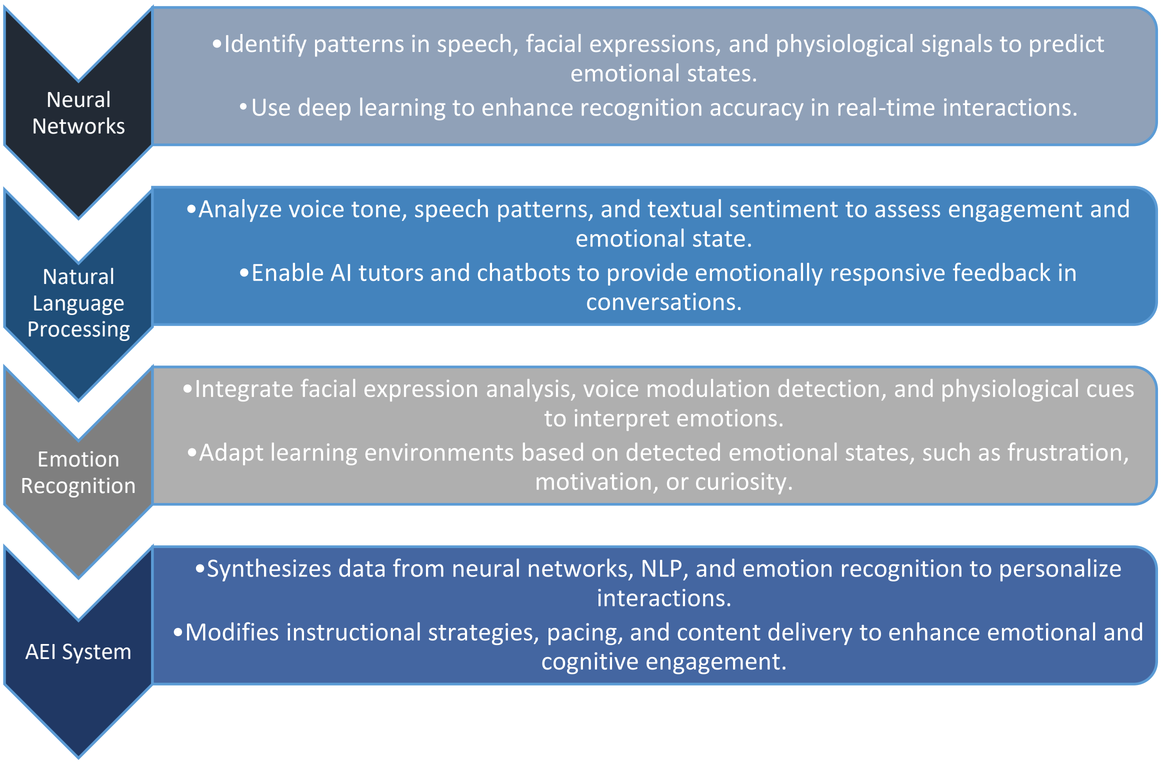

Figure 2. Neural networks and NLP in AEI

STEM to STEAM and the Art of Intelligent Machines

The integration of AEI in robotics marks a pivotal shift in how machines interact with humans, particularly in educational settings. While traditional AI has enabled automation and computational efficiency, AEI enhances robotics with emotional recognition and responsiveness, fostering deeper engagement in learning environments (Fernández Herrero et al., 2023; Marcos-Pablos & García-Peñalvo, 2022). A broader understanding of how AEI-powered robotics supports interdisciplinary learning requires an examination of the historical foundations of STEM and its evolution in education.The foundation of STEM education can be traced back to the mid-20th century, with a strong national emphasis on scientific and technological advancements following the launch of the Soviet Union's Sputnik satellite in 1957 (Granovskiy, 2018). Concern over the United States' scientific and engineering capabilities led to the creation of the National Aeronautics and Space Administration (NASA) in

1958, followed by major federal initiatives to strengthen STEM education (Mohr-Schroeder et al., 2015). The release of *A Nation at Risk* (1983) heightened awareness of educational reform, stressing the necessity of science, mathematics, and technological literacy to maintain global competitiveness (Mohr-Schroeder et al., 2015). These efforts culminated in Project 2061, which established science literacy benchmarks, followed by White House STEM initiatives in 2009 and 2010 (Mohr-Schroeder et al., 2015).

Global adoption of STEM education reinforced its role in preparing students for 21st-century challenges (Rifandi & Rahmi, 2019). Traditional STEM frameworks centered on science, technology, engineering, and mathematics were developed to enhance problem-solving skills, critical thinking, and innovation (Widya et al., 2019). Expanding research on cognitive and emotional learning prompted educators to recognize the value of artistic and creative disciplines, leading to the emergence of STEAM education. Integrating the arts into STEM curricula provided a more holistic approach that emphasized creativity, design, and interdisciplinary thinking (Dignam, 2024b; White, 2014).

An educational model that balances scientific inquiry, artistic expression, and emotional intelligence reflects the evolving demands of a technology-driven yet human-centered society. Philosophical STEAM education aligns with emerging advancements in AI and AEI, where empathetic, socially aware robotics play a vital role in shaping student engagement and interdisciplinary learning (Breiner et al., 2012). The blending of the arts in STEAM education and AEI-powered robotics and STEAM education transect and fosters emotionally intelligent and dynamic learning environments.

The Human Element in STEAM Education

The transition from STEM to STEAM education acknowledges that scientific and technological advancements are most impactful when they incorporate human expression, creativity, and emotional intelligence. Traditional STEM disciplines prioritize technical expertise and analytical problem-solving, while the integration of the arts introduces an essential human element, allowing students to connect deeply with content through creativity and emotional engagement (Dignam, 2024b; Perignat & Katz-Buonincontro, 2019).

The arts serve as a conduit for personal expression, cultural storytelling, and innovative thinking, enriching STEM learning by making abstract concepts tangible and emotionally resonant (Leavy et al., 2023). Through visual arts, music, drama, and creative writing, students explore scientific and mathematical principles in ways that transcend rote memorization, fostering a deeper, more intuitive grasp of complex ideas. Educational approaches that embed narrative elements and creative problem-solving have been shown to increase motivation, engagement, and retention of knowledge (Erol et al., 2023).

The power of storytelling within STEAM enhances students' imagination and problem-solving abilities and mirrors the core function of AEI for recognizing, interpreting, and responding to human emotions (Erol et al., 2023). Art allows learners to form emotional connections to their studies, and AEI-driven robotics enhances educational experiences by adapting to students' affective states, fostering motivation, and deepening engagement. Integrating artistic elements within STEM disciplines has been shown to strengthen cognitive, social, and emotional learning, enriching students' ability to connect abstract scientific concepts with personal experiences (Dignam, 2024b).

The personalization afforded by AEI aligns with the transformative potential of STEAM, where students are encouraged to integrate emotional and creative dimensions into their learning (Larkin, 2015). Understanding how the arts evoke emotional connections makes it clear that AEI and STEAM education share a common goal of humanizing learning through emotion, perception, and creativity (Leavy et al., 2023). The integration of music and artistic expression into STEM education further supports engagement by fostering deeper intellectual curiosity and cognitive flexibility (Dignam, 2024b). As interdisciplinary and transdisciplinary frameworks continue to evolve, the intersection of STEAM and AEI presents a novel pathway for nurturing leadership, social-emotional learning, and problem-solving abilities across various educational settings (Dignam, 2024a).

Emotional Connections in STEAM

Science, technology, engineering, art, mathematics education, and AEI-driven robotics create meaningful emotional connections by allowing students to engage with content in creative, expressive, and immersive ways. The integration of the arts, storytelling, and digital expression within STEM disciplines has demonstrated its ability to strengthen cognitive engagement and social-emotional learning (Leavy et al., 2023). Artificial emotional intelligence enhances student interactions by adapting to emotional cues, storytelling, and artistic expression, providing avenues for students to connect with learning material on a personal level. These elements become even more impactful when approached through interdisciplinary and transdisciplinary education, which encourages synthesis across multiple disciplines to create deeper, more meaningful learning experiences (Barth et al., 2023; Liao, 2016).

Figure 3 illustrates the interconnected relationship between STEAM education, AEI and robotics, storytelling and digital expression, and emotional connections through SEL. Each quadrant of the clover-shaped Venn diagram represents a distinct yet complementary domain that contributes to an adaptive and emotionally intelligent learning environment. Positioned in the north, STEAM education emphasizes innovation, creativity, critical thinking, and problem-solving, equipping students with the skills necessary for interdisciplinary exploration. To the south, AEI and robotics focus on emotion recognition, adaptive AI, and personalized learning, enabling technology to respond to students' affective states and foster engagement. On the east side, storytelling and digital expression integrate narrative learning, multimodal engagement, and the arts, offering students opportunities to construct meaning, communicate complex ideas, and engage in creative inquiry. The west quadrant highlights emotional connections and SEL, which fosters empathy, motivation, social-emotional learning, and personalized growth, reinforcing the human-centered aspects of education.

The center of the figure represents the fusion of these four domains, emphasizing emotionally intelligent, interdisciplinary, and creative learning environments. Integrating STEAM education with AEI-driven robotics allows students to engage in inquiry-based and problem-solving experiences that are both technologically advanced and emotionally responsive. Storytelling and digital expression strengthen the connections between knowledge and lived experiences, reinforcing deeper engagement and critical thinking. Emotional connections and SEL ensure that learning remains meaningful, culturally relevant, and personalized to students' needs. The convergence of these elements creates a balanced educational model that supports intellectual curiosity, social awareness, and creative problem-solving, preparing students to navigate complex challenges with adaptability and emotional intelligence.

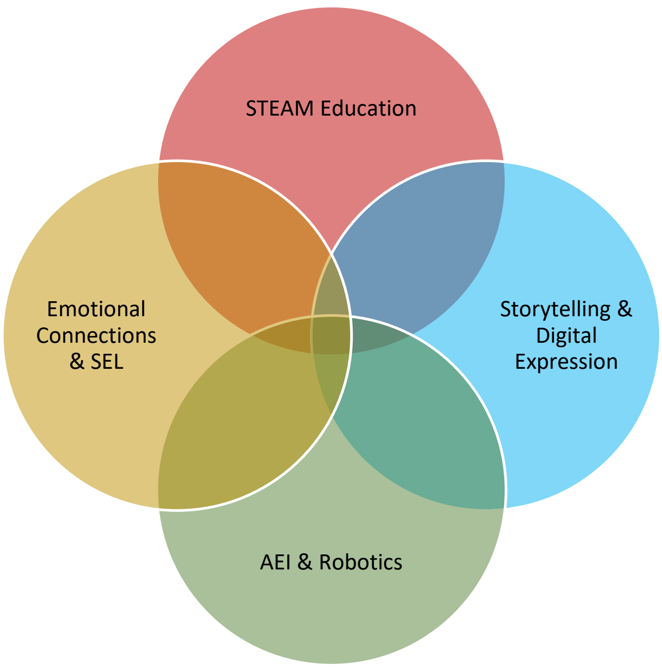

Figure 3. STEAM, AEI, storytelling, and SEL connections

Interdisciplinary and Transdisciplinary Learning in STEAM

Interdisciplinary and transdisciplinary approaches are essential to modern STEAM education, as they promote synthesized learning experiences that connect traditionally disparate fields. Interdisciplinary learning involves the blending of multiple subject areas, allowing students to draw insights across different disciplines to solve complex problems (Yang et al., 2022).

For example, a STEAM lesson may integrate engineering principles with artistic design, enabling students to engage in creative problem-solving that mirrors real-world innovation (Liao, 2016). Transdisciplinary learning moves beyond subject integration to create seamless, holistic educational experiences that prioritize real-world applications and learner-driven inquiry (Clark & Button, 2011). A transdisciplinary approach fosters collaboration between domains, preparing students to address complex challenges that require adaptability, critical thinking, and innovation (Barth et al., 2023).

Digital storytelling serves as a key tool within interdisciplinary and transdisciplinary STEAM education, allowing students to craft narratives that merge technology, personal experience, and academic content (Yang et al., 2022). Robotics and AI-driven learning platforms expand this storytelling potential by offering emotionally intelligent, interactive experiences that enable students to engage with content innovatively (Jia et al., 2023). Research indicates that students engaged in digital storytelling within interdisciplinary projects demonstrate enhanced critical thinking, creativity, and collaboration, as they must synthesize ideas across disciplines (Dignam, 2024a).

The emotional connections formed through STEAM storytelling and AEI-powered robotics reinforce the importance of teaching and learning approaches that emphasize collaboration, creativity, and human-centered engagement. Interdisciplinary and transdisciplinary learning, emotional intelligence, and digital storytelling will continue to redefine educational methodologies, ensuring that STEAM education remains dynamic, relevant, and deeply connected to students' lived experiences (Clark & Button, 2011; Barth et al., 2023).

The Art and Science of Learning through Experience

Vygotsky (1978) posits student acquisition of knowledge results through social interactions, resulting in the construction of knowledge. Vygotsky's constructivist paradigm links students' social interactions during hands-on activities, such as interacting with AI robotics, to constructing meaningful understanding for knowledge-building. Kolb et al. (1984) theorized the act of learning includes a four-part cycle that includes concrete experience, reflective observation, abstract conceptualization, and active experimentation for acquiring knowledge. In addition, cognition via experiential learning is exemplified when students demonstrate knowledge by applying concepts, such as during robotics, to learning (Kolb, 2014). Constructing and experiencing are key for meaningful STEAM-AEI knowledge building.

Interdisciplinary and transdisciplinary approaches in STEAM education establish a foundation for deeper engagement in discovery learning, experiential learning, and constructivism. These pedagogical frameworks emphasize hands-on, student-centered learning that fosters critical thinking and real-world problem-solving. Kolb's experiential learning model, which includes concrete experience, reflective observation, abstract conceptualization, and active experimentation, aligns with interdisciplinary and transdisciplinary STEAM education by providing students with opportunities to engage in inquiry-based learning that connects theory to practice (Kolb, 2014; Nguyen et al., 2020).

Social constructivist learning theory, particularly Vygotsky's perspective, accentuates the importance of collaboration, dialogue, and the co-construction of knowledge. The Zone of Proximal Development (ZPD) suggests that students learn best when engaging in tasks slightly beyond their current ability, supported by peers or instructors (Saleem et al., 2021; Vygotsky, 1978). Interdisciplinary and transdisciplinary STEAM learning fosters cooperative inquiry, where students actively construct knowledge through experiential learning and digital storytelling (Remington et al., 2023).

Discovery learning, a concept advanced by Bruner (1996) and Piaget (1972), reinforces problem-solving and active exploration in education. Within STEAM disciplines, students engage in design challenges requiring hypothesis formation, experimentation, and refinement of understanding (Efgivia et al., 2021). Transdisciplinary learning advances this concept by removing rigid subject barriers, integrating real-world contexts, and promoting holistic approaches to knowledge acquisition (Jia et al., 2023).

Kolb's experiential learning theory emphasizes the need for meaningful engagement, encouraging students to cycle through experiencing, reflecting, conceptualizing, and applying knowledge to new situations (Kolb et al., 1984; Nguyen et al., 2020). Active participation in hands-on learning environments within STEM and STEAM education reinforces the practical application of knowledge, strengthening students' ability to construct understanding through real-world interactions (Budiyanto et al., 2020).

A deeper sense of agency in learning develops through discovery learning, experiential learning, and constructivism in interdisciplinary and transdisciplinary STEAM education. Robotics, AEI, and digital storytelling further enhance this process by providing interactive, emotionally responsive learning experiences that bridge disciplines and foster creativity (Saleem et al., 2021). Integrated approaches to education ensure that students develop both technical competencies and the ability to think critically, adaptively, and creatively in an evolving world (Remington et al., 2023).

Sense of Agency in Learning

Figure 4 illustrates the role of Sense of Agency in Learning as the central force connecting six key learning approaches that empower students to take ownership of their education. Positioned at the center, Sense of Agency in Learning represents adaptability, innovation, and student-driven learning, emphasizing how individuals actively engage with content, apply knowledge, and navigate challenges in meaningful ways. Each surrounding element contributes to fostering a sense of agency by providing distinct yet interconnected pathways for exploration, application, and reflection.

Discovery Learning, located at the top (12 o'clock), serves as the entry point for exploration, inquiry, and hypothesis testing. Positioned at 2 o'clock, Experiential Learning reinforces real-world application, allowing students to engage hands-on with concepts and refine their understanding through practice and reflection. Constructivism, situated at 4 o'clock, highlights the social and cognitive dimensions of learning by promoting collaborative meaning-making and critical thinking. At 6 o'clock, Digital Storytelling integrates creativity, narrative engagement, and multimodal expression, enabling students to personalize their learning experiences. Artificial Emotional Intelligence (AEI), placed at 8 o'clock, fosters emotionally responsive and adaptive interactions, ensuring that students remain engaged, supported, and motivated in learning. Finally, Robotics, positioned at 10 o'clock, enhances problem-solving through technology-driven experiences, encouraging students to develop computational thinking and hands-on engineering skills. Together, these six elements interconnect at the center, where agency is cultivated through interdisciplinary and transdisciplinary learning, reinforcing the importance of student autonomy, engagement, and innovative thinking in STEAM education.

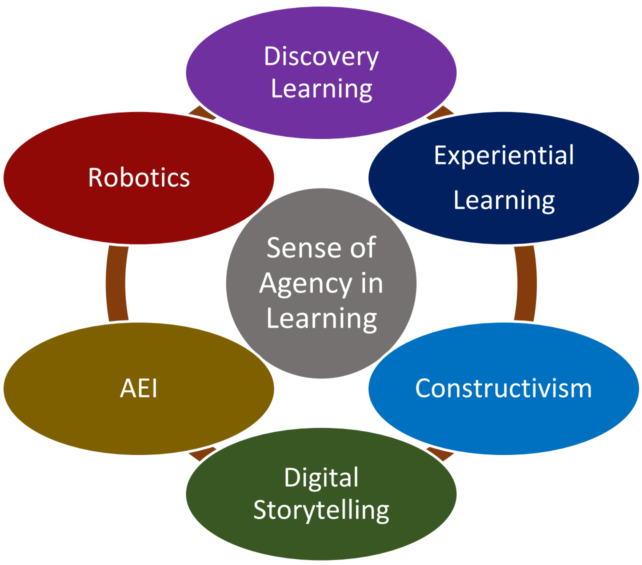

Figure 4. Sense of agency in learning

The Role of Robotics in Experiential Learning

Educational robotics serves as a powerful tool for fostering experiential learning, aligning with constructivist principles that emphasize active engagement and real-world application. Robotics-based activities encourage students to develop problem-solving skills, enhance critical thinking, and engage in collaborative learning environments where they can test hypotheses and refine their approaches (Miglino et al., 1999). When students interact with programmable robots and AI-driven systems, learners move beyond passive consumption of information, instead taking on the role of designers, engineers, and computational thinkers (Uslu et al., 2023).

Research indicates that AI and robotics significantly impact cognitive, social-emotional, and intellectual learning outcomes, reinforcing their role as essential components of experiential education (Salas-Pilco, 2020). Robotics platforms designed for educational use enhance student motivation, engagement, and adaptability, providing a bridge between theoretical knowledge and real-world application (Hsu et al., 2021). These tools create an iterative learning cycle where students can prototype, test, and refine solutions, reinforcing the engineering design process while fostering growth in computational thinking and problem-solving skills.

Beyond cognitive benefits, robotics cultivates social-emotional learning by promoting teamwork, communication, and adaptability. Collaborative robotics projects encourage students to negotiate roles, share ideas, and navigate challenges, mirroring real-world interdisciplinary problem-solving scenarios (Uslu et al., 2023). Additionally, AEI-powered robotics enhances personalized learning experiences by adapting to students' affective states, responding to their needs, and providing emotionally intelligent feedback that reinforces persistence and resilience (Salas-Pilco, 2020).

The integration of robotics in experiential learning environments possesses the potential to bridge STEM concepts with real-world applications, ultimately preparing students for future careers that require adaptability, creativity, and interdisciplinary thinking. As AI and AEI-driven robotics continue to evolve, their impact on educational methodologies and student engagement offers new pathways for authentic, hands-on learning experiences across all levels of education.

Integration of Robotics in Early Childhood Education

Robotics in early childhood education serves as an engaging tool for fostering cognitive, social, and technological development. Research indicates that introducing robotics at an early age enhances problem-solving abilities, computational thinking, and creativity, positioning young learners to develop essential twenty-first-century skills (Zviel-Girshin et al., 2020). Through hands-on engagement with robotics, children build confidence in technology use while simultaneously strengthening their ability to work collaboratively and think critically. Programs that integrate educational robotics into early learning environments have demonstrated positive outcomes in children's ability to engage with engineering concepts in meaningful ways, reinforcing the role of robotics as a developmental asset (Canbeldek & Isikoglu, 2022).

The combination of robotics and STEAM education in early childhood provides children with opportunities to develop computational thinking through interactive and play-based learning. Robotics activities allow young learners to experiment with sequencing, algorithmic design, and logical reasoning, creating a foundation for later STEM learning (Chaldi & Mantzanidou, 2021). Research further emphasizes the importance of early childhood educators' perspectives in shaping how robotics is introduced in preschool and primary education settings (Gavrilas et al., 2024).

The willingness of teachers to integrate robotics into early childhood education influences both student engagement and curriculum design, emphasizing the necessity for teacher preparation and ongoing professional learning in educational robotics. As a result, children exposed to robotics programs demonstrate higher levels of engagement and motivation in problem-solving tasks, making the integration of robotics in early education a promising strategy for fostering early digital literacy and creativity (Papadakis et al., 2021).

Robotics also facilitates experiential learning by enabling children to interact with digital tools in ways that connect with their natural curiosity. Coding and robotics programs tailored for early childhood have been shown to enhance both cognitive and social development by promoting exploratory learning environments (Canbeldek & Isikoglu, 2022). The hands-on nature of robotics supports inquiry-based learning while fostering collaboration among young learners, ultimately enhancing problem-solving and decision-making skills (Chaldi & Mantzanidou, 2021). Research suggests that early exposure to robotics fosters confidence in using technology, leading to long-term benefits as children progress through their education (Gavrilas et al., 2024). Through these interactive experiences, young children gain early exposure to technological fluency, setting the stage for continued engagement with STEAM fields as they advance academically.

Fostering Critical Thinking and Teamwork in K-12 Education

Educational robotics has become an essential tool in kindergarten through twelfth-grade (K-12) education, fostering critical thinking and teamwork through hands-on, inquiry-based learning experiences. Research highlights the role of robotics in engaging students in computational problem-solving while developing their ability to analyze, design, and implement creative solutions (Jurado et al., 2020). The integration of robotics into the curriculum provides students with opportunities to work collaboratively on STEM-related projects, reinforcing both cognitive and interpersonal skills (Safrudin et al., 2021). Robotics activities in classrooms encourage iterative learning, where students test hypotheses, troubleshoot errors, and refine their approaches, ultimately strengthening their ability to think critically and work effectively within teams (Sisman et al., 2021).

Collaboration is central to educational robotics, as students must communicate ideas, delegate responsibilities, and collectively resolve challenges throughout the design and programming process (Jurado et al., 2020). In many cases, students engage in structured group work where roles such as programmer, builder, and researcher are assigned, requiring them to practice both leadership and cooperation skills (Fonseca et al., 2020). Studies indicate that a programmer, builder, researcher, and collaborative dynamic not only improves problem-solving capabilities but also enhances students' confidence in STEM subjects, particularly among those who may initially feel apprehensive about technology-focused learning (Sisman et al., 2021).

Beyond fostering critical thinking, robotics education is pivotal in preparing students for future careers that demand interdisciplinary competencies. The use of robotics in K-12 settings has been shown to improve spatial reasoning, logical thinking, and creativity. An intrinsic ability to engage in spatial reasoning, logical thinking, and creativity is a key element of both STEM education and broader workforce readiness (Safrudin et al., 2021).

Robotics curricula frequently incorporate elements of design thinking, engineering principles, and algorithmic logic, providing students with a multifaceted learning experience that bridges theoretical knowledge with practical application (Fonseca et al., 2020). As robotics continues to be integrated into modern classrooms, its potential to support holistic student development through collaborative and inquiry-based learning remains a key area of focus for educators and policymakers.

Incorporating Robotics in Higher Education

Robotics has become an integral component of higher education, particularly in engineering, computer science, and STEAM disciplines. Universities are increasingly embedding robotics into curricula to promote hands-on learning, problem-solving, and innovation-driven education (Ahmad, 2020). A scenario-based approach to integrating robotics into coursework prepares students for future workforce demands, ensuring that graduates develop practical skills in automation, artificial intelligence, and interdisciplinary collaboration (Kucuk & Sisman, 2020). Robotics education at the university level often employs project-based and challenge-based learning models, allowing students to engage in real-world problem-solving and industry-relevant applications (Tselegkaridis & Sapounidis, 2021).

The use of robotic simulators and physical robotic platforms enables students to develop technical competencies in coding, mechanics, and AI-driven automation without the limitations of hardware constraints (Tselegkaridis & Sapounidis, 2021). Research suggests that the integration of robotics in university settings enhances student engagement and motivation, particularly when combined with experiential learning approaches (Conde et al., 2021). Studies also highlight that students with prior exposure to robotics in pre-kindergarten through twelfth-grade (PK-12) settings demonstrate increased confidence and performance in higher education robotics courses, reinforcing the value of early exposure and continued application throughout a student's academic trajectory (Kucuk & Sisman, 2020).Beyond technical skill development, robotics in higher education fosters collaborative learning and interdisciplinary, transdisciplinary exploration. Programs that incorporate robotics within STEAM and AI curricula emphasize the intersection of technology, creativity, and problem-solving, allowing students to work across disciplines and develop adaptive learning strategies (Cox, 2021). As AI continues to evolve, robotics courses increasingly integrate AI-driven decision-making models, preparing students to apply ML, automation, and human-robot interaction principles to real-world applications (Ahmad, 2020).

The ongoing expansion of robotics in higher education curriculum design is significant in preparing students for the demands of modern industries. Research supports the need for institutional investment in robotics laboratories, interdisciplinary programs, and AI-enhanced learning tools to ensure that students gain the skills necessary for an increasingly automated world (Conde et al., 2021). As universities continue to refine their robotics offerings, collaborative partnerships between academia and industry will further strengthen opportunities for students to engage in cutting-edge research, internships, and applied learning experiences that bridge theory and practice (Cox, 2021).

Table 2 provides an overview of how robotics, AI, and AEI are applied across different educational levels, from early childhood to higher education. The table outlines the distinct applications of robotics and AI at each stage, emphasizing their role in fostering problem-solving, computational thinking, teamwork, and interdisciplinary learning. Artificial Emotional Intelligence-driven systems further enhance these experiences by providing emotionally responsive interactions that adapt to students' needs, supporting engagement, motivation, and personalized learning. The progression of robotics and AI across educational levels illustrates how these technologies evolve to meet increasingly complex cognitive, social, and technical demands. Table 2 serves as a comparative reference for examining the developmental impact of robotics and AI integration throughout the educational continuum.

Table 2. Robotics, AI, and AEI across education levels

Educational Level	**Robotics & AI Applications**	**Key Benefits**	**AEI Integration**
Early Childhood	Play-based robotics, coding tools	Enhances problem-solving, computational thinking, creativity	Emotionally responsive interactions to support engagement and early learning
K-12 Education	STEM/STEAM robotics projects, collaborative programming	Develops critical thinking, teamwork, and design-based problem-solving	AEI-driven feedback for adaptive learning and motivation
Higher Education	AI-powered robotics, interdisciplinary applications	Advances technical proficiency, research skills, and workforce readiness	Human-robot interaction, AI decision-making models, and ethical AI considerations

Conceptual Framework

The integration of artificial emotional intelligence (AEI) and robotics in education is grounded in constructivist, experiential, interdisciplinary, and transdisciplinary learning theories, which emphasize active engagement, social interaction, and adaptive learning. A constructivist, experiential, interdisciplinary, and transdisciplinary framework synthesizes research on AI, robotics, and emotional intelligence to examine how AEI-powered systems enhance student motivation, engagement, and collaboration while addressing the pedagogical challenges associated with emerging technologies.

A constructivist perspective encapsulates the value of hands-on, inquiry-based learning, where students construct knowledge through interaction with adaptive technologies. Vygotsky's (1978) Zone of Proximal Development (ZPD) highlights the importance of scaffolded and interactive experiences aligning with robotics education, where learners engage in exploration, experimentation, and iterative problem-solving. Artificial Emotional Intelligence enhances this process by enabling emotionally responsive interactions, reinforcing student engagement and self-regulated learning. The ability of AEI-powered robotics to recognize affective cues, adjust responses, and support perseverance in problem-solving tasks introduces a dynamic, student-centered feedback loop. Kolb's (2014) experiential learning theory further supports the integration of AEI robotics, emphasizing the cyclical nature of learning through concrete experience, reflective observation, abstract conceptualization, and active experimentation. Robotics-based activities align with this model as students engage with technology, analyze feedback, and refine solutions in an iterative manner. The introduction of AEI in robotics expands experiential learning by providing emotionally attuned interactions, fostering greater motivation and deeper cognitive engagement.

Interdisciplinary and transdisciplinary STEAM education frameworks provide another foundational layer for AEI robotics. The inclusion of science, technology, engineering, the arts, and mathematics supports creativity, innovation, and holistic learning (Perignat & Katz-Buonincontro, 2019). The artistic and emotional dimensions of STEAM align with AEI's ability to humanize technology, allowing students to develop cognitive and emotional connections to their learning experiences. Digital storytelling, robotics-based artistic projects, and adaptive AI tutors illustrate how AEI enhances creative problem-solving within STEAM disciplines.

The conceptual framework developed in this study positions AEI-powered robotics at the hub of constructivist, experiential, interdisciplinary, and transdisciplinary learning theories. Emotionally intelligent robotics extends beyond automation by fostering adaptive, socially responsive, and emotionally aware learning environments across early childhood, K-12, and higher education. The application of AI, emotion recognition, and human-computer interaction creates new opportunities to enhance engagement, collaboration, and personalized learning pathways.

Results and Discussion

The integration of AEI and robotics in education presents significant findings related to student engagement, cognitive development, social-emotional learning, and interdisciplinary applications. The analysis examines how AEI-driven robotics enhances learning experiences across early childhood, K-12, and higher education, emphasizing its role in personalized instruction, adaptive learning environments, and collaboration.

Impact of AEI and Robotics on Student Engagement and Motivation

Artificial intelligence and AEI-driven robotics contribute to heightened student engagement and motivation, particularly by fostering interactive, responsive, and adaptive learning environments. Emotionally intelligent robotics adjusts instructional strategies based on learners' affective states, reinforcing personalized learning experiences and increasing persistence in problem-solving tasks (Salas-Pilco, 2020; Uslu et al., 2023). The ability of AEI to adapt in real-time enhances engagement by addressing student frustration and maintaining curiosity, which aligns with constructivist and experiential learning theories (Bruner, 1997; Kolb, 2014; Piaget, 1972; Vygotsky, 1978).

Artificial Emotional Intelligence-powered robotics demonstrates particular effectiveness in early childhood settings, where interactive and play-based learning strengthens cognitive and emotional engagement. Research indicates that young learners respond with increased enthusiasm when robotics is introduced through storytelling, hands-on problem-solving, and peer collaboration, which supports early STEM literacy (Gavrilas et al., 2024). Similarly, studies highlight that PK-12 students engaged in robotics-infused learning environments exhibit greater motivation and perseverance, particularly when collaborative projects and gamified challenges are incorporated (Jurado et al., 2020). In higher education, robotics integration promotes self-directed learning, equipping students with critical thinking skills and technological proficiency necessary for careers in AI, engineering, and interdisciplinary research (Kucuk & Sisman, 2020).

Cognitive Development and Interdisciplinary Learning Outcomes

Findings indicate that robotics supports cognitive development by reinforcing computational thinking, logical reasoning, and problem-solving skills. Engaging students in iterative design cycles where learners construct, test, and refine solutions fosters metacognitive growth and higher-order thinking abilities (Safrudin et al., 2021). Artificial Emotional Intelligence further enhances cognitive engagement by incorporating emotionally responsive interactions, ensuring that learning remains personalized and adaptive (Perignat & Katz-Buonincontro, 2019). At the early childhood level, robotics enhances spatial reasoning and algorithmic thinking by encouraging interactive play and hands-on exploration. Research suggests that young children who engage in robotics-based learning environments develop foundational skills in logic, coding, and digital literacy, positioning them for future STEM engagement (Canbeldek & Isikoglu, 2022; Chaldi & Mantzanidou, 2021).

For PK-12 learners, robotics integrates abstract STEM concepts with creative problem-solving, reinforcing design thinking and interdisciplinary collaboration (Dignam, 2024a). Engaging in robotics competitions and team-based engineering challenges improves student confidence in problem-solving and computational reasoning, further strengthening interdisciplinary learning (Sisman et al., 2021). At the higher education level, robotics serves as a catalyst for cross-disciplinary innovation, allowing students from computer science, engineering, arts, and cognitive sciences to explore human-robot interaction, ethical AI applications, and adaptive learning research (Cox, 2021). The inclusion of robotics-integrated curricula enhances students' analytical reasoning and professional readiness, equipping learners with the interdisciplinary competencies needed for emerging AI-driven fields (Ahmad, 2020).

Social-Emotional Learning and Human-Robot Interaction

AEI-powered robotics significantly contributes to SEL by fostering emotionally responsive, cooperative, and communicative learning environments. Studies suggest that emotionally intelligent robotics encourages students to develop teamwork, empathy, and social awareness, reinforcing the importance of collaborative problem-solving (Salas-Pilco, 2020). For early childhood learners, interactive robotics programs support emotional regulation and peer collaboration, particularly through structured play and cooperative storytelling (Gavrilas et al., 2024). Studies indicate that young learners engaged with emotionally responsive robots develop greater social awareness, improved communication skills, and increased confidence in peer interactions (Papadakis et al., 2021).

Within PK-12 education, AEI-powered robotics enhances team-based learning, where students negotiate roles, solve problems collectively, and strengthen leadership skills. Research highlights that robotics-integrated SEL interventions improve students' ability to manage conflict, engage in effective communication, and collaborate on complex challenges (Jurado et al., 2020; Sisman et al., 2021). In higher education, robotics programs incorporating human-robot interaction (HRI) frameworks enable students to explore adaptive AI, emotional intelligence in technology, and ethical considerations in AI-human collaboration (Tselegkaridis & Sapounidis, 2021). Studies indicate that students engaging with AEI-driven robotics acquire skills in ethical AI design, human-centered engineering, and interdisciplinary problem-solving, preparing them for leadership in technology and education (Kucuk & Sisman, 2020).

Challenges and Considerations for AEI-Powered Robotics in Education

The integration of AEI-powered robotics presents challenges related to ethical concerns, accessibility, and technological limitations. Privacy issues surrounding emotion recognition algorithms, as well as affective computing, require continued refinement to ensure welcoming learning experiences (Hudson, 2023). Research highlights that cultural and linguistic differences must be addressed in AEI robotics to positively influence emotional assessments and student feedback (Marcos-Pablos & García-Peñalvo, 2022).

Findings also indicate that disparities in robotics access are derived from underfunded schools and rural communities. While robotics adoption has increased at the higher education level, accessibility remains limited in early childhood and K-12 settings, where resource constraints and professional growth gaps affect implementation (Dignam, 2024a). Educators and policymakers must prioritize infrastructure development, teacher training, and ethical AI frameworks to ensure responsible integration of AEI-powered robotics. Future research should continue exploring adaptive learning models, interdisciplinary AI applications, and human-robot interaction, shaping the ongoing evolution of robotics in education (Conde et al., 2021).

Conclusion

The integration of AEI in educational robotics presents new possibilities for enhancing student engagement, cognitive development, and SEL across early childhood, K-12, and higher education settings. Emotionally intelligent robotics supports personalized, adaptive instruction by recognizing affective cues and adjusting responses, accordingly, reinforcing constructivist and experiential learning approaches. The findings of this study suggest that AEI-powered robotics fosters curiosity, problem-solving, and interdisciplinary collaboration while also addressing social-emotional competencies through cooperative learning experiences. Students interacting with emotionally responsive robotics develop enhanced motivation, perseverance, and self-regulated learning behaviors, reinforcing the potential for AI-driven systems to support both academic and personal growth.

Despite its benefits, the implementation of AEI-powered robotics requires careful consideration of ethical, accessibility, and pedagogical challenges. The refinement of emotion recognition technologies remains essential to ensure that AEI-driven systems provide accurate assessments of student affective states. Addressing disparities in access to robotics-based education is necessary to ensure access to technology-enhanced learning environments. Additionally, educators require specialized training to effectively integrate AI and robotics into classroom instruction, ensuring that adaptive learning models align with best practices in pedagogy and interdisciplinary education.

Artificial emotional intelligence represents a shift toward a more human-centered approach to educational robotics, prioritizing adaptive, emotionally attuned interactions that enhance engagement, collaboration, and cognitive development. Future research on human-robot interaction, interdisciplinary applications, and ethical considerations will be instrumental in shaping the responsible integration of AEI-powered robotics in educational settings. A commitment to ongoing evaluation, refinement, and professional growth will ensure that emotionally intelligent AI systems remain valuable tools in fostering meaningful, student-centered learning experiences.

Recommendations

The advancement of AEI-powered robotics in education necessitates further research and strategic implementation to maximize its potential while addressing ethical and pedagogical concerns. Emotion recognition technologies must be refined to identify a range of affective expressions, making it imperative that AEI algorithms are trained to recognize and respond to emotional variations with accuracy and precision. Transparent AI development and interdisciplinary collaboration will contribute to more ethically guided robotics applications in education.

The expansion of robotics access in early childhood, K-12, and higher education settings remains a priority to prevent disparities in technology-enhanced learning. Schools and universities must invest in infrastructure that supports the integration of AI and robotics within interdisciplinary and transdisciplinary curricula, ensuring that students have opportunities to engage in robotics-based learning. Teacher preparation programs should incorporate training in AI literacy and robotics pedagogy, equipping educators with the knowledge and skills necessary to facilitate adaptive, emotionally responsive instruction. Professional growth initiatives should provide ongoing support for educators, reinforcing best practices in interdisciplinary and transdisciplinary teaching and experiential, constructivist learning models that align with AI-enhanced education.

Interdisciplinary and transdisciplinary education offer opportunities for integrating AEI-powered robotics within broader learning frameworks. Emotionally intelligent robotics supports the fusion of STEM, the arts, and human-centered AI applications, allowing students to explore connections between technology, creativity, and social-emotional learning. Digital storytelling, interactive design, and human-robot collaboration provide avenues for deepening engagement and fostering critical thinking in students. The continued exploration of AEI within interdisciplinary education will contribute to a more dynamic and adaptive learning environment that strengthens students' ability to navigate complex, real-world challenges.

Ongoing research into human-robot interaction will be essential for refining the role of AEI-powered robotics in education. Longitudinal studies that examine student engagement, academic achievement, and SEL outcomes will provide valuable insights into the effectiveness of emotionally intelligent AI systems. Exploring applications for AEI in special education can further enhance personalized learning opportunities, allowing adaptive robotics to support students with diverse needs through individualized feedback and scaffolding. Ethical considerations related to AI-driven emotional recognition, privacy, and decision-making should remain central to discussions on the integration of AEI in education.

A comprehensive approach to AEI-driven robotics in education requires collaboration among educators, researchers, and policymakers to ensure responsible and effective implementation. Prioritizing transparency and interdisciplinary and transdisciplinary learning will contribute to a more transformative educational landscape where emotionally intelligent robotics enhances both cognitive and social-emotional development.

Scientific Ethics Declaration

The authors declare that the scientific, ethical, and legal responsibility of this article published in JESEH journal belongs to the authors.

Conflict of Interest

The authors declare that they have no conflicts of interest

Funding Declaration

The authors did not receive support from any organization for the submitted work.

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